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The Role of Cognitive Effort in Decision Performance Using Data Representations :;a Cognitive Fit Perspective

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THE ROLE OF COGNITIVE EFFORT IN DECISION PERFORMANCE USING DATA REPRESENTATIONS: A COGNITIVE FIT PERSPECTIVE

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DEDICATION

To Johanna, my wife, my love, my best friend and my better half. To Maja and Karl, my amazing children - they have been there for me for the last five years. Thank you for your love, support and encouragement.

To Ivan and Danica Bačić, my parents and Maša Yurasko, my sister – they are my foundation.

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Words cannot express how much I love you all. This is a tribute to all of you.

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ABSTRACT

A major goal of Decision Support (DSS) and Business Intelligence (BI) systems is to aid decision makers in their decision performance by reducing effort. One critical part of those systems is their data representation component of visually intensive applications such as dashboards and data visualization. The existing research led to a number of theoretical approaches that explain decision performance through data representation's impact on users' cognitive effort, with Cognitive Fit Theory (CFT) being the most influential theoretical lens. However, available CFT-based literature findings are inconclusive and there is a lack of research that actually attempts to measure cognitive effort, the mechanism underlying CFT and CFT-based literature. This research is the first one to directly measure cognitive effort in Cognitive Fit and Business Information Visualization context and the first one to evaluate both self-reported and physiological measures of cognitive effort. The research provides partial support for CFT by confirming that task characteristics and data representation do influence cognitive effort. This influence is pronounced for physiological measures of cognitive effort while it minimal for self-reported measure of cognitive effort.

While cognitive effort was found to have an impact on decision time, this research suggests caution is assuming that task-representation fit is influencing decision accuracy. Furthermore, this level of impact varies between self-reported and physiological cognitive effort and is influenced by task complexity. Research provides extensive cognitive fit theory, business information visualization and cognitive effort literature review along with implications of the findings for both research and practice.

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CHAPTER I

1. INTRODUCTION

Organizations are facing challenges of information complexity and uncertainty (Zack, 2007). In that indeterminable world organization members need to make frequent decisions. A major goal of Decision Support Systems (DSS) and Business Intelligence (BI) systems is to aid decision makers in their decision performance by reducing effort (Benbasat & Todd, 1996). One critical part of those systems is their data representation component of visually intensive applications such as dashboards and data visualization. These applications are cognitive tools (Hovis, 2002) requiring from users to deploy various levels of cognition and effort to leverage them in the process of decision making. This link is confirmed though multiple research streams that suggest a relationship between decision performance quality and data representation. The combined research led to a number of theoretical approaches that explain decision performance through data representation's impact on users' cognitive effort (Vessey, 1991a). Recently, those theoretical approaches, namely matching of presentation format to a task as subscribed by Cognitive Fit Theory (Vessey, 1991a; Vessey & Galletta, 1991) have been unable to fully explain the empirical results. Despite its significant use within organizations, academic Information Systems (IS) research focused on data representation and its impact on decision makers' cognition and effective decision making is still underdeveloped.

The lack of progress is not limited to research only. Design format choices often labeled as "chartjunk" (Tufte, 1983) continue to exist in practice and are enabled by both vendors and dashboard designers. The frequent inappropriate use of information presentation formats (Few, 2006; Tractinsky & Meyer, 1999) continues to lead to suboptimal decisions (Amer & Ravindran, 2010). Further amplifying the practical significance of this research is the reality of users being asked to make decisions in the age of Big Data and resulting information overload, where the role of systems such as business dashboards that filter and separate important information from noise is becoming critical (Hovis, 2002).

While current research suggests the theoretical role of cognition (effort and overload) as a mechanism to explain the efficiency and the effectiveness of data representation in decision making, there is a lack of research that actually attempts to measure this mechanism and incorporate it with other elements that shape users' cognition. Given this research gap, along with (i) inability of available literature to offer more conclusive results (addressed in later chapters), (ii) the importance and proliferation of data representation use in business practice, and (iii) noted tendency for 'chartjunk' designs, forms a motivational foundation behind this research. The goal of the research is to further explore and expand our understanding of how data representation impacts decision performance (efficiency and effectiveness) by focusing on cognitive effort along with other relevant, theoretically supported variables such as task, presentation format and user characteristics, namely tendency to engage in and enjoy effortful cognitive activity.

In addition to significant research implications given identified gaps, I suggest that even larger implications are possible for practitioners. However, in order to obtain a more complete understanding of practical implications of this research, it is important to contextualize it within data representation context that is relevant to practice: application tools such as dashboards and data visualizations. The expectation level for these tools to aid in today's business decision making setting cannot be underestimated:

> "Dashboards and visualization are cognitive tools that improve your "span of control" over a lot of business data. These tools help people visually identify trends, patterns and anomalies, reason about what they see and help guide them toward effective decisions. As such, these tools need to leverage people's visual capabilities. With the prevalence of scorecards, dashboards and other visualization tools now widely available for business users to review their data, the issue of visual information design is more important than ever. (Hovis, 2002)"

Even a decade ago statistics cited that over 50% of surveyed companies were implementing dashboards (Leon, 2003). According to a CIO Insight survey of 215 senior business managers (in companies with revenues of $500 million or more) by 2007, 62% of managers were actually using dashboards (CIO Insight, 2007). The importance of these tools has been echoed in a recent survey of large group of CIO's and business executives as visualization and dashboards combined have been reported as the top trend in BI (Howson, 2010).

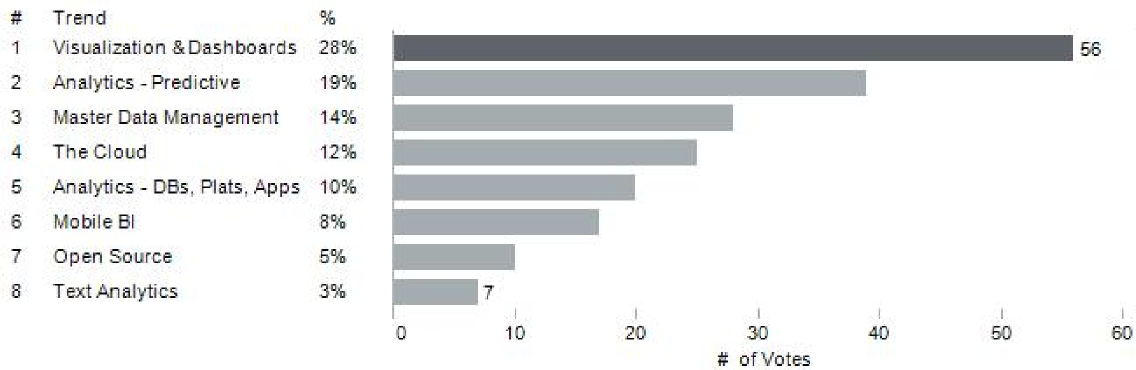


Figure 1: Top Trends in BI

Although tremendously popular and adopted by most businesses today, most dashboards fall short of their potential to communicate efficiently and effectively. This is largely not due to technological inadequacies but rather due to poor design (Few, 2006) ranging from inappropriate use of design elements such as color, symbols, and 3D display to more fundamental issue of data representation format choice such a tabular vs. graphical format. Despite those warnings of poor design, vendors continue to mainly focus on technology capabilities of real time data, use of multiple sources, interactivity, customization and optimization. Users are given the ability to design their own visualization while at the same time they were never trained or informed of how to effectively display data (Few, 2006).

In this practical context of data representation tools, executives, managers and knowledge workers make decisions daily and frequently. Their decision making performance is important for their professional and organizational success. The future of their organizations is dependent on both individual and cumulative effect of their decisions in terms of decision timelines and quality. Since organizations strive to make decisions that are rooted in data and information, it is not surprising that data representation is critical in the ability to support decision making performance. Hence, given research gaps as well as the ubiquity of data representations in business decision making, improvements in understanding of factors influencing users' cognitive effort and subsequent decision performance could offer significant practical value. On one hand, having greater understanding of how and through which relationships data representation impacts decision makers' cognitive effort will aid designers in selecting appropriate presentation formats, features and capabilities. On the other hand, data visualization and dashboard vendors will be provided with a key component and feedback input to their development cycle. The ability to understand and focus on how new product capabilities, modifications and enhancements impact users' cognitive effort will offer a way to evaluate and prioritize product feature changes.

This theory-based empirical research leverages key accumulated knowledge from Business Information Visualization and Cognitive Theory-centered literature as well as related Human-Computer Interactions (HCI), Cognitive Psychology and DSS fields. Business Information Visualization literature emphasizes, in theoretical terms, that appropriateness of data representation influences decision making performance because of its impact on decision makers' perception and cognition. Furthermore, the literature provides evidence that that the effectiveness of a specific presentation format depends on the *task* that is being performed (Desanctis, 1984; Jarvenpaa & Dickson, 1988; Speier, 2006; Speier, Vessey, & Valacich, 2003; Vessey, 1991a; Vessey, 1991b). For example, even relatively early IS literature recognized the goal of the information systems designer to develop information systems to be appropriate for both *the task* at hand and the characteristics of the decision maker (Benbasat & Dexter, 1985) *(emphasis added)*. The importance of the role of task in selecting the most appropriate data representation has been recognized by most Information Visualization literature and it resulted in the inclusion of task as a critical component in Cognitive Fit Theory (Vessey, 1991a).

Therefore, this research also provides detailed literature review of Cognitive Fit Theory – a native IS theory that came about as a reaction to the inability to rationalize the findings from previous research (Vessey, 1991a) - encompassing both theoretical and empirical components of the theory. In the context of the theory, this research highlights evidence of inconclusive results on the role of data representation/task fit in decision making, especially when dealing with more complex tasks (Frownfelter-Lohrke, 1998; Speier, 2006) often facing decision makers in business settings (Dennis & Carte, 1998). It also confirms the importance of cognitive effort as a mechanism that links data representation with performance while emphasizing the appropriateness to approach task from both complexity (simple vs. complex) and representation lens (spatial vs. symbolic).

Having identified the criticality of cognitive effort, this research establishes connection with extant DSS and HCI literatures that is suggesting a notion that cognitive effort plays an important role in how information systems are used (Djamasbi, 2007) as there is evidence that people use information systems to reduce cognitive effort (Todd & Benbasat, 1992, 1994). Furthermore, cognitive effort-focused literature (Cognitive Psychology) suggests that that the impact of cognitive effort on decision performance may be influenced by user's Need for Cognition or tendency to engage in and enjoy effortful cognitive activity, Therefore, Need for Cognition is incorporated into this research. While not central to the research, I recognize that all decision tasks are contextualized in its own domain(s). Therefore, the research intends to account for potential influence of *domain (business) knowledge* on cognitive effort and decision performance.

As a result of relevant literature analysis, the existing research fails to actually (i) measure the impact of data representation on cognitive effort and (ii) assess the impact of users' cognitive effort on decision making efficiency and effectiveness. Given the significant theoretical role of users' cognitive effort in the data representation literature, the lack of more nuanced and empirical support for that notion represents a major shortcoming and offers potential to clarify some of research and practical dilemmas. Therefore, I suggest that by adopting a direct recognition of the cognitive effort it may be possible to move beyond existing inconclusive results. Moreover, I suggest that the role of cognitive effort needs to be understood before further extensions and adaptations of existing cognition-based theories are offered to domains outside of original theory-building environment, as is has been already done in a number of instances. The original environment that gave rise to the dominant viewpoint centered on

Cognitive Fit Theory consisted of empirical research that compared decision performance in simple tasks across tabular and graphical presentation formats. This was an example of grounded theory building and, as such could be significantly dependent on the context and environment that was created in. Hence, I suggest that the extension of theory to other domains could be premature if the underlying mechanism, cognitive effort, is not understood and measured in an improved manner.

While the first data collection (study #1) will be primarily focused on traditional experimental design and data gathering, recent advances in eye tracking technology make it feasible to more objectively measure levels of cognitive effort that an individual is extending when observing and engaging with visual display. However, most eye tracking research up to this point has been limited to understanding consumer and user behavior within retailing Web space. Meaningful application and analysis of eye tracking technology to BI and DSS is very limited, yet given the importance of BI/DSS to organizational success it represents an opportunity for a new research stream. This study intends, therefore, to enhance the validity of traditional data gathering and analysis by planning to incorporate eye tracking technology in a second data collection (study #2) effort, which adds another pioneering dimension to the research.

In summary, in order to address the identified gap, this study is attempting to answer a number of related research questions within the context of business decision making and data representation:

- Does data presentation format impact cognitive effort?

- Does task characteristic impact cognitive effort?
- Is there interplay between data presentation format and task characteristic on users' cognitive effort? Is there an impact of cognitive effort on decision performance?
- Is there an impact of user characteristics, namely Need for Cognition on cognitive effort and decision performance?
- What are the effective ways of measuring cognitive effort in the context of this research?

With those questions in mind, Section II highlights important findings from the literature related to Business Information Visualization, Cognitive Fit Theory, and Cognitive effort. This literature informs suggested Research Model and Hypothesis Development in Section III. Section IV details methodologies deployed to test the hypotheses. Section V provides results and analysis. Section VI offers discussion of the results along with research and practical implications. Section VII describes known limitations and future research, both as a result of those limitations and of direct findings from this research. Concluding remarks are presented in Section VIII.

CHAPTER II

2. LITERATURE REVIEW

2.1 Business Information Visualization

One critical part of systems used to assist in decision making (DSS) and dealing with more complex business problems (BI) is their data representation component. In business setting data representation is often delivered though visually intensive applications such as dashboards and data visualization. These applications are cognitive tools (Hovis, 2002) that are informed by and find its academic roots in interlinked subfields that literature labeled as Graphical display, Data Visualization, Information Visualization, Business Information Visualization and Visual Analytics. This section offers more in-depth state of the field as it provides guidance through terminology, historical development and more recent key research findings.

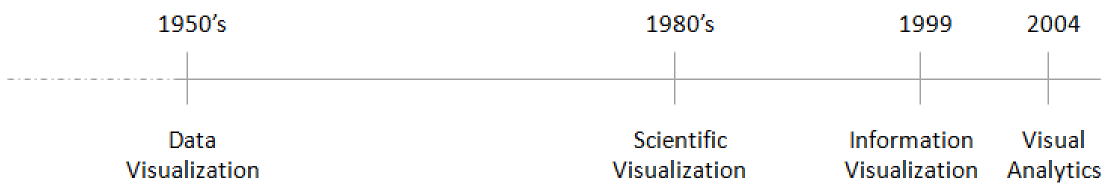
Both literature and practice use various forms of term ‘visualization’, partly due to the lack of knowledge and partly due to the overlapping nature of the subfields (Lurie & Mason, 2007). Definitional understanding provides value as it ensures clarity in scope and appropriate contextualization of research and its practical implications. Following the overview of terminology, historical perspective of key research events is offered as it (i) provides the necessary insight that many data representation developments are very recent given that the history of the field dates back times before computers and information technology platforms, and (ii) highlights the criticality of tabular vs. graphical presentation format for DSS and BI systems. Lastly, more current and influential literature is reviewed as it informs and grounds this research through the knowledge associated with the building block of data representation elements (color, symbols, display dimensionality, etc...), human cognition and perception principles (Gestalt principles, human memory limits, Information chunking, five plus minus two...) that are leveraged as strategies to enhance task-presentation fit and influence users' cognitive effort.

2.1.1 Background and Terminology

A number of terms related to visualization of data are available, such as Visualization (in general), Data Visualization, Information Visualization (InfoViz), Scientific Visualization, Visual Analytics, Business Visualization (BizViz). These terms are not necessarily mutually exclusive and have been sometimes used inconsistently (Lurie & Mason, 2007). Virtual reality is another form of visualization; however, it is not within the scope of this research. Figure 2 presents a timeline of visualization terms and fields related to Visualization.

Visualization is an old concept, examples of which date back 32,000 years ago with cave drawings in France (Clottes, 2000). Visualization in general, has been defined as the process of representing data as a visual image (Schroeder, Martin, & Lorensen, 1996).

Figure 2: Visualization Timeline



Data Visualization emerged is the 1950s with the advent of computer graphics (Post, Nielson, & Bonneau, 2002) and is defined as the science of visual representation of "data", defined as information which has been abstracted in some schematic form, including attributes or variables for the units of information (Friendly & Denis, 2001) .

Scientific Visualization was used initially to refer to visualization as a part of a process of scientific computing: the use of computer modeling and simulation in scientific and engineering practice (Post et al., 2002) . The discipline emerged in the late 1980s as a key field in computer science and in numerous other application domains such as geoscience, meteorology, and medicine. Scientific visualization provides processes for steering the data set and seeing the unseen, thereby enriching existing scientific methods (Zhang, 2001). Encyclopedia Britannica defines it as process of graphically displaying real or simulated scientific data (Encyclopedia-Britannica).

Information Visualization has been coined in 1999 as the use of computer-supported interactive visual representations of abstract data to amplify cognition (Card, Mackinlay, & Shneiderman, 1999). Typical examples of abstract data that has no inherent mapping to space are employee turnover statistics, bank branch deposit growth data or sales goals figures. This paper adopts Card et al.'s definition to Business Information Visualization (BIV) by defining it as the use of computer-supported interactive visual representations of abstract *business* data to amplify cognition.

Visual Analytics is the science of analytical reasoning facilitated by interactive visual interface (Chabot, 2009; Thomas & Cook, 2005). The formation of the U.S. Department of Homeland Security National Visualization and Analytics Center (NVAC) in March 2004 resulted in increased interest in the field of visual analytics (Kielman, Thomas, & May, 2009). The publication of Illuminating the Path: The R&D Agenda for Visual Analytics in 2005 marked the formal beginning of the field. The initial domain driving the development of this discipline was Homeland Security and is currently being applied in security, health, commerce, transportation, energy, food/agriculture, insurance and personal domains. It is often described as dealing with complex data that enables detection of the expected and discovery of the unexpected (Thomas & Kielman, 2009).

2.1.2 Business Information Visualization Research History

In order to better understand the current state of BIV, it is important to understand the development of the field throughout the history and its link to related disciplines. While the term Information Visualization has been coined in 1999 (Card et al., 1999), it is important to recognize that the history of the field dates back times before computers and information technology platforms.

One of the first clear-cut uses of information related graphics occurred about 3800 BC in Egypt, a crude map in clay showing agricultural properties in Mesopotamia (Lester, 2000). In 2nd century Egyptians used tabular data visualization to organize astronomical information and to aid navigation. In 10th/11th century there is a first evidence of showing data change over time in a graphical format. The next significant event related to visual representation of abstract data can be traced back to first geographic maps without statistical information dating from 12th century in China depicting the map of the tracks of Yu the Great (Tufte, 1983).

It was not until the 17th century that two dimensional visual grids were first used purely to represent numbers. They were introduced by Rene Descartes, in his La Geometrie (Descartes, 1637), as a means to visually numbers as grid coordinates(Few, 2004). First visualization of statistical data occurred in 1644 by Michael Langren, showing distances between Toledo and Rome. Through works of J.H. Lamber (Lamber, 1779) and William Playfair (Playfair, 1801), graphical design was at last no longer dependent on direct analogy to the physical world (Tufte, 1997)-a major event for development of Information Visualization. Snow’s visual representation of the data clearly showed the deaths from cholera in central London clustering around a single location, leading to the elimination of the outbreak . In 1869, Minard created an infographic, which is often called ‘the best statistical graphic ever drawn”, showing Napoleon’s march to Moscow and horrific retreat with effective use of direction, two-dimensional surface, temperature and time scales (Lester, 2000; Tufte, 1983).

In 1920s statistical and psychology research community continued addressing various methods of presenting quantitative information (Eells, 1926; Huhn, 1927; Washburne, 1927a, 1927b). By the mid-1930s, the enthusiasm for visualization had been succeeded by the rise of quantification and formal models in the social sciences and some refer to the period from 1900 to 1949 as the period of ‘Modern Dark Ages’ for visualization (Friendly & Denis, 2001).

The innovative data visualization research remained effectively dormant until a ‘perfect storm’ occurred with Tukey’s call for recognition of data analysis as a separate discipline (Tukey, 1962), the birth of computer technology and Bertin’s (Bertin, 1967) attempt to “classify all graphic marks in terms how they could express data”(Ware, 2000). In late 1960s and early 1970s there was documented use of computer –based graphical presentations of business information (Miller, 1969; Morton, 1967; Shostack & Eddy, 1971). The research of display methods can be traced back to 1970s and Tukey through his research in display of related statistical data (Tukey, 1972, 1977). During the same decade, Management Information System (MIS) and Management academics are starting to explore presentation format as a variable in MIS designs and research frameworks (Benbasat & Schroeder, 1977; Chervany & Dickson, 1974; Dickson, Senn, & Chervany, 1977; Mason & Mitroff, 1973; Zmud, 1979).

The real influence of Bertin's work occurred after translation of his original work to English in 1983 (Bertin, 1983) when statistical and quantitative theme continued in 80s with William Cleveland (Cleveland, 1985) and Edward Tufte (Tufte, 1983). In 1986 we have the first proposal developed of an application-independent presentation tool that automatically designs effective graphical presentations (Mackinlay, 1986). The cognitive perspective of information visualization came to forefront in the same period with works by Stephen Kosslyn (Kosslyn, 1989) and Tufte (Tufte, 1990) and others. Some of the early notable academic papers dealing with graphical information presentation and computer graphics occurred in the same period (Benbasat & Dexter, 1985, 1986; Davis, Benbasat, Dexter, & Todd, 1986; Desanctis, 1984; Ives, 1982; Lucas Jr, 1981; Lucas Jr & Nielsen, 1980) with implications on decision making being analyzed. The introduction of cognitive fit theory by Vessey (Vessey, 1991a; Vessey, 1991b; Vessey & Galletta, 1991) and its application of computer interactions (Shaft & Vessey, 2006) to visual display of data and its effectiveness further accelerated research of visualization and information presentation format (Dilla, Janvrin, & Raschke, 2010; Huang et al., 2006). The influence of Cognitive Fit Theory based literature continues in 21st century as it is currently the dominant lens through which researchers assess the impact of data representation on performance. Table 1 (adapted from (Friendly & Denis, 2001)) provides abbreviated summary of significant events and individuals that informs and influences the field of Business Information Visualization.

Stage	Timeline	Significant Event	Significant Individual
Early Visualization	3800 BC	A crude map in clay showing agricultural properties in Mesopotamia	
	2nd Century	Egyptians used tabular data visualization to organize astronomical information and to aid navigation	
	10/11th Century	A first evidence of showing data change over time in a graphical format	
	12th Century	First geographic maps without statistical information (in China depicting the map of the tracks of Yu the Great)	
17th - 19th Century	1637	Two dimensional visual grids to purely to represent numbers	Renee Descartes
	1644	First visualization of statistical data showing distances (b/w Toledo and Rome)	Micheal Landgren
	1686	One of the first data (weather) maps was portrayal of wind directions	Edmond Halley
	Late 1700's	One of the first to use time-series charts in scientific writings	J.H. Lamber
	1800's	Pioneered the use of area to depict quantity, invented bar and pie charts and was the first to use time-series to depict economic data	William Playfair
	1854	An early and most worthy use of maps to chart patterns of disease was the famous dot map of cholera epidemic in London	John Snow
	1864	Portrayal of exports of French wine by showing quantity as well as direction to the data measures located on the world map	Charles Minard
	1869	Infographic, which is often called 'the best statistical graphic ever drawn"	Charles Minard
20th Century	1926	Research on quantitative information presentation in statistics	W.C. Eels
	1927		J.N. Washburne
	1927		R. V. Huhn
	1962	Call for Data Analysis discipline separate from statistics	J.W.Tukey
	1963	Classification of all graphic marks in terms how they could express data	Bertin
	1972-1977	Statistical data display and exploratory data analysis	J.W.Tukey
	early 1980's	Computer graphical displays	Various
	1983	Quantitative information visualization	Edward Tufte
	1985		William Cleveland
	1986	First tool that automatically designs effective graphical presentations	J. Mackinlay
	1989	Use of cognitive psychology in visualization	Stephen Kosslyn
	1989		Edward Tufte
	1991	Cognitive Fit Theory proposed	Iris Vessey
	1999	Term Information Visualization coined	S. Card, J.Mackinley
2=1st Century	2000		C. Ware
	2004-2005	Introduction of Visual Analytics	J.J. Thomas and K.A.Cook

Table 1: Visualization - Historical Overview

2.1.3 BIV Current State and Key Research Findings

With emergence of Information Visualization and Business Intelligence, a new discipline called Business Information Visualization came to life in the last 10 years, drawing from historical experiences, events and disciplines such as the ones described in the historical overview. Business Information Visualization (BIV) is a relatively new incarnation of visualization and has just started to gain researchers' and practitioners' attention (Zhang, 2001). The value of information visualization depends on the success of its applications and the value of its application in business has been recognized before (Wright, 1998); however, suggestions were made that visualization in business applications is about ten years behind visualization in the sciences (West, 1995). A number of definitions exist for Business Information Visualization. Tegarden (1999) defines it as “simply the use of visualization technologies to visualize business data or information (p.8)”. He also recognizes that “business information has been visualized in the form of tables, outlines, pie charts, line graphs, and bar charts for a very long time and that today business information visualization means the use of multidimensional graphics to represent business-related data or information”(Tegarden, 1999 p.18). Zhang offers a more detailed definition of Business Information Visualization as "a process of creating appropriate computer-generated visual representations of large amounts of non-geometric managerial data for human problem-solving and decision-making support"(Zhang, 2001 p.4).

Most of the existing Information Visualization and BIV research was viewed through the lens of information representation and interaction (Bacic & Henry, 2012). Information representation or spatial representations that are derived from symbolic data (Card et al., 1999) has been researched extensively and a large part of it centered on understanding the significance of representation formats. In dashboard context, data representation can be viewed through the prism of representation methods (histograms, tables, bar charts, bullet graphs, etc...), representation elements (color, text, symbols, size, etc...) and representation layout/position. Table 2 offers a sample of current and often used data representation methods for decision making.

Presentation Format		Purpose
Table	Presentation Table	Highlighting key figures
	Reference Table	Presenting larger volume of data for referencing
Chart	Bar Chart	Comparison of values acress categories
	Stacked Bar Chart	Comparison of segements of total
	Line Chart	Visualization of trends in data over time
	Pie Chart	Showing the percentage distribution variable
	Parallel Coordinates	Plotting multi-dimensional large data on parallel axes and connecting with lines
Plots	Scatter Plots	Showing the relationship between two variables
	Stem-and-Leaf Plots	Assessing a distribution of collection of numbers
	Q-Q plots	Comparing two probability distributions by graphing their quantiles
Map	Flow Maps	Depicting the movement of a quantity in space / time
	Chlorepleth Maps	Visualization of patterns across space
	Dot Maps	Visualization of the location and density of phenomenon using symbols
	Proportional Maps	Displaying a phenomenon attached to a point within the spatial unit
Networks	Force-directed Layouts	Understaning the structure of a general unidirected graph
	Arc Diagrams	One-dimensional identification of connections
	Matrix Views	Rapid perception of links
Diagrams	Node link diagram	Revealing position in hierarchy though solid nodes and links
	Adjacancy diagram	Revealing position in hierarchy through solid areas
	Enclosure diagram	Displaying hierarchies through containment (treemaps)

Table 2: Sample Presentation Formats

What this research calls data representation format others have called metaphor (Tegarden, 1999), techniques (Huang et al., 2006), display format (Dilla & Steinbart, 2005), visualization components (Viegas, Wattenberg, van Ham, Kriss, & McKeon, 2007), views (Mackinlay, Hanrahan, & Stolte, 2007), presentation format (Benbasat, Dexter, & Todd, 1986a; Ives, 1982) and presentation mode (Benbasat & Dexter, 1986). Data representation format research largely focused on understanding the impact of display choice between tabular and graphical (Amer, 1991; Benbasat & Dexter, 1985, 1986; Benbasat & Schroeder, 1977; Cleveland, 1985; Desanctis, 1984; Dilla & Steinbart, 2005; Eells, 1926; Harvey & Bolger, 1996; Ives, 1982; Jarvenpaa & Dickson, 1988; Lucas Jr, 1981; Lucas Jr & Nielsen, 1980; Remus, 1984). Furthermore, the literature provides evidence that that the effectiveness of a specific presentation format depends on the task that is being performed (Desanctis, 1984; Jarvenpaa & Dickson, 1988; Speier, 2006; Speier et al., 2003; Vessey, 1991a; Vessey, 1991b). It has been noted (Baker, Jones, & Burkman, 2009) that this body of research resulted in formulation of Cognitive Fit Theory (Shaft & Vessey, 2006; Vessey, 1991a; Vessey, 1991b; Vessey & Galletta, 1991), that suggests the importance of fit between the problem representation and the problem-solving task in achieving effective performance. This theory continues to be used today (Adipat, Zhang, & Zhou, 2011; Baker et al., 2009; Bin & Watts, 2010; Dilla et al., 2010; Dull & Tegarden, 1999; Huang et al., 2006; Jarupathirun & Zahedi, 2007; Kelton, Pennington, & Tuttle, 2010; Weiyin, Thong, & Kar Yan, 2004).

In addition to representation formats and the role of task, researchers created a significant body of knowledge around representation elements such as color (Benbasat & Dexter, 1985, 1986; Benbasat et al., 1986a; Benbasat, Dexter, & Todd, 1986b; Cleveland, 1985; Davis et al., 1986; Tufte, 1990; Ware, 2000), object depth and dimensionality (Dull & Tegarden, 1999; Kumar & Benbasat, 2004; Tractinsky & Meyer, 1999; Watson & Driver, 1983) and organization, symbols labels, text, icons, lines, grids, axes (Bertin, 1983; Cleveland, 1985; Ives, 1982; Kosslyn, 1989) suggesting the significance of representation elements on BIV effectiveness.

Most visualization research focused on data representation is based upon theories of human perception and cognition. Miller (1956) describes human perceptual ability in terms of judgments about unidimensional and multidimensional stimuli. The ability to decode stimuli is prerequisite to visualization use (Cleveland, 1985). This decoding process occurs in part due to visual perception abilities in which we exploit our visual channel inputs without creating an overload. Baker et al. (2009) introduce the view in which cognition incorporates only post-perceptual processing of information such as internal representations and the role of human memory. Similarly, cognitive science suggests that users have internal representations of visualizations they see and that external representation should take this into consideration (Liu & Stasko, 2010). The importance of memory when presenting and processing information visually is widely acknowledged (Bin & Watts, 2010; Schmell & Umanath, 1988) hence the use of design principles leveraging memory is well documented

(Tegarden, 1999). The issue of limited amount of information storable in short term memory is central to many design constraints. An effective way to increase the amount of information in short-term memory called "chunking" has often been applied (Miller, 1956; Tufte, 1990). The choice of colors (Benbasat et al., 1986b) and symbols (Bertin, 1983) is often done in consultation with memory and cognition literature. The majority of information visualization literature is in agreement with Tufte (1983) in suggesting that effective data representation leverages the mechanism of amplified human perception and cognition to reduce Information Overload and non-data noise.

In summary, having provided overview of terminology and historical context, the literature review focused on Business Information Visualization offers key takeaways that guide and inform the remaining content of this research. First, there is an increasing number of presentation formats deployed in business decision making with research primarily being focused on the impact of tabular vs. graphical representation. Second, research suggests, in theoretical terms, that the appropriateness of data representation influences decision making performance because of its impact on decision makers' perception and cognition. Third, highlighted literature provides the evidence that the effectiveness of a specific data representation depends on the task that is being performed. Fourth, Cognitive Fit Theory is currently the dominant theoretical lens through which researchers assess the impact of data representation on performance.

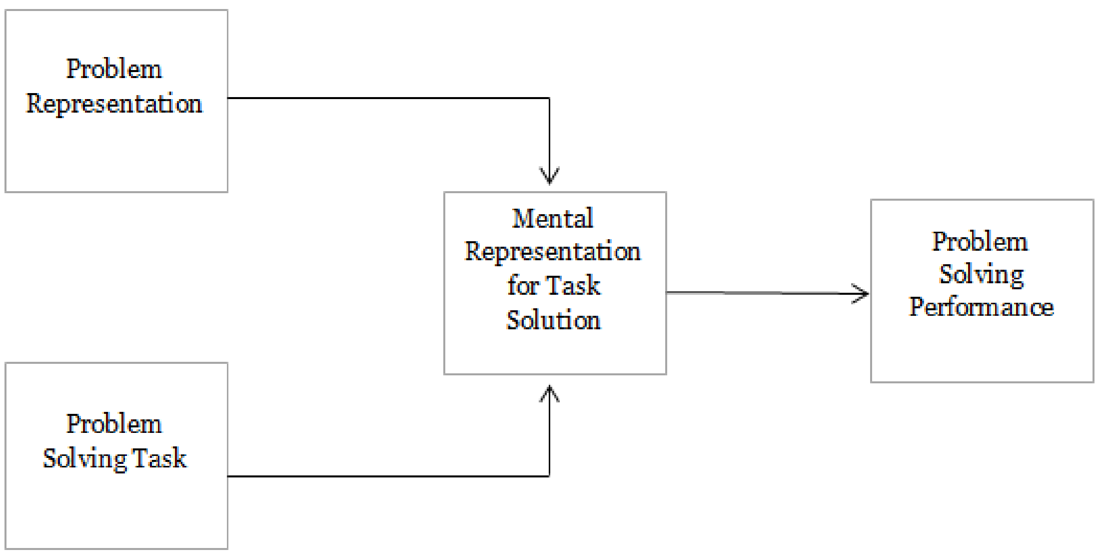
Guided by above findings, this research proceeds with an in-depth review of available Cognitive Fit Theory-based literature - encompassing both theoretical and empirical components of the research. Furthermore, important findings are summarized and key gaps identified helping to inform the research model.

2.2 Cognitive Fit

2.2.1 Cognitive Fit Theory

In the context of data presentation and decision performance, early research on the role of task has been inconsistent. A series of studies, starting with Minnesota experiments compared decision efficiency and effectiveness in variety of tasks by offering subjects information required for decision making in tabular and graphical formats. Cognitive Fit Theory (CFT) by Vessey (1991b) attempted to explain the inconsistencies of the prior research (Kelton et al., 2010) by attributing performance differences of presentation formats on different tasks to how well the presentation format matches the task in hand (Baker et al., 2009). That is, according to the original CFT, there was a direct link between task type and presentation format. According to the original CFT, a suggestion was offered were if both the problem representation and the problem-solving task involve the same cognitive style, then there is said to be a "cognitive fit" between them. Cognitive fit between the problem representation (presentation format) and the problem-solving task occurs "when the problem-solving aids (problem representation among them) support the task strategies required to perform that task" (Vessey, 1991a), 220). Therefore, matching the representation to the task leads to use of similar problem-solving processes and form a match with formulated mental representation for task solution. In other words, individuals develop mental representation of the task and adopt decision processes based on the task and the presentation of task information (Vessey, 1991a; Vessey & Galletta, 1991). As a result, the performance depends upon the fit between information presentation, task, and decision processes used by the decision maker.

Figure 3: Original CFT (Vessey, 1991)

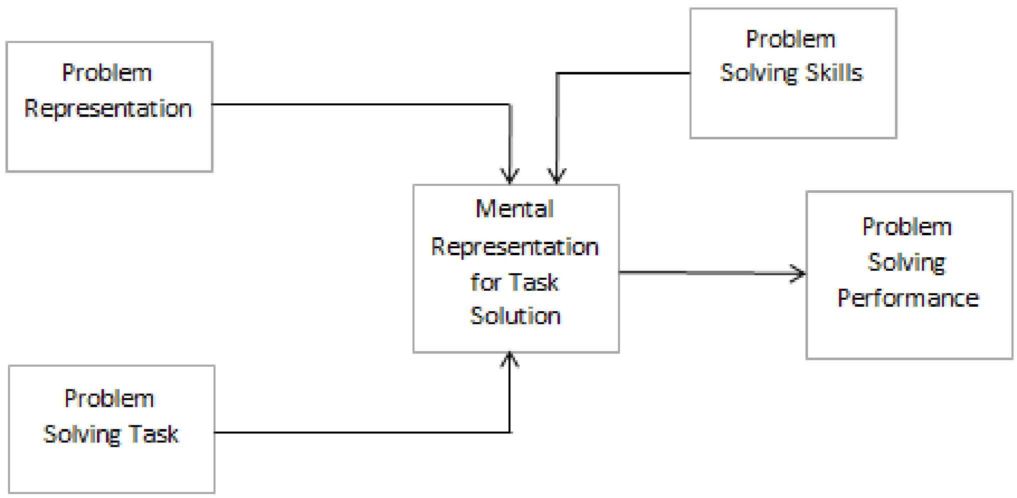


When the information emphasized by the presentation matches the task, decision makers can use the same mental representation and decision processes for both the presentation and the task, resulting in faster and more accurate solutions (Vessey, 1991a). When a mismatch occurs, one of two processes will occur. First, decision makers may transform the presented data to better match the task, which might increase the time needed and might decrease accuracy because any transformation can introduce errors (Vessey, 1991a). Alternatively, decision makers may adjust their decision processes to match the presentation, decreasing accuracy and increasing time because the information does not match the ultimate needs of the task (Perrig and Kintsch 1985).

Without a match between the problem representation and the task, the decision maker must either convert the representation to a form similar to the task or convert the task to the form similar to the representation, leading to inefficient decision making (Vessey & Galletta, 1991). Vessey (1991a) argued that the development of a link between format presentation and task characteristics would be difficult due to the large number of characteristics and the many ways in which they have been described. Her solution was to use a two-category classification based on cognitive style and task requirements. She classified tasks into two cognitive types: spatial and symbolic. Spatial tasks consider the problem area as a whole rather than as discrete data values and require making associations or perceiving relationships in the data. Symbolic tasks, on the other hand, involve extracting discrete, and precise, data values (Vessey & Galletta, 1991) .

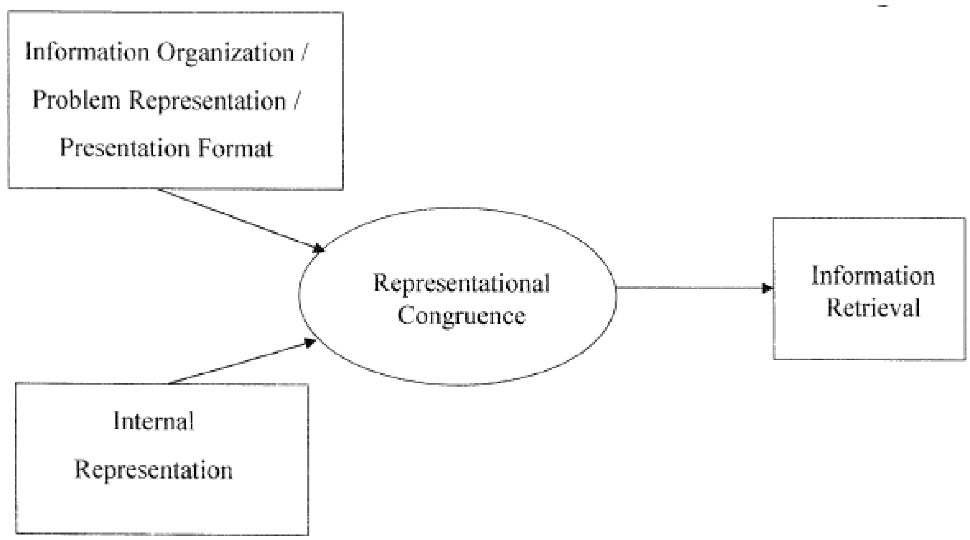
The original theory was expanded a number of times to attempt to further explain problem solving performance. In another study, Vessey and Galletta (1991) examined the effects of the match between three elements—problem solving skill, problem representation, and problem-solving task—on problem-solving performance (See Figure 4). The problem-solving tasks they used were spatial and symbolic tasks, while the problem representation dimension included graphs and tables. Both spatial and symbolic subject skills were measured. From their results, the authors concluded that the effectiveness of a problem representation varied with the type of task to be solved. They also found that performance improved when subject skills matched either the task or both the problem representation and the task. No performance improvements were noted when skills matched the problem representation alone.

Figure 4: Modified CFT – Vessey and Galletta (1991)



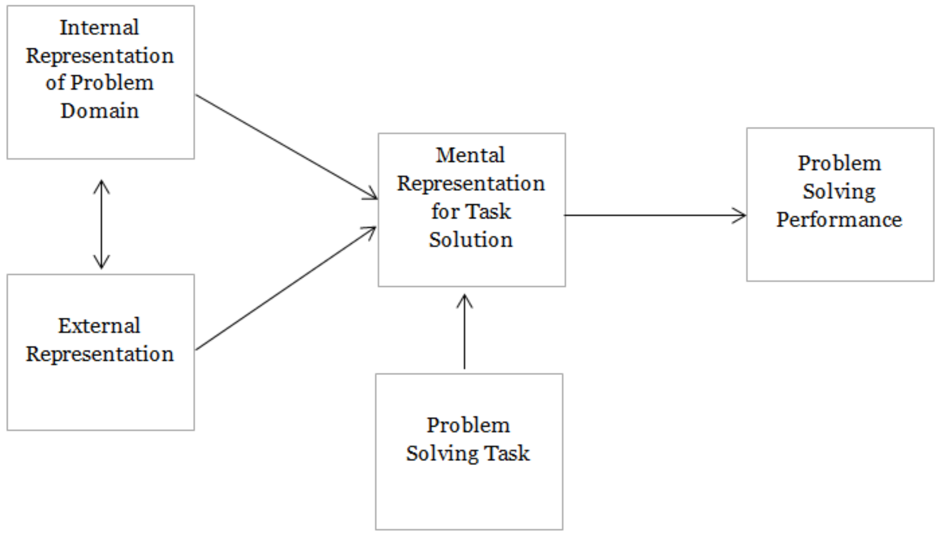
Building on CFT's notion that suggests fit resulting in a better problem solving performance, Chandra and Krovi (1999) extended the concept of cognitive fit to also account for the congruence between the external information and the internal representation of the user (Figure 5). Authors extended existing theory to account for the congruence between information organization and internal representation. Their study investigated the effect of organization of information presented to the user on the retrieval performance and found that information is differentially represented for making effective and efficient retrieval and that designers need to consider retrieval when delivering systems and information. This extension is also known as the Theory of Representational Congruence.

Figure 5: Theory of Representational Congruence



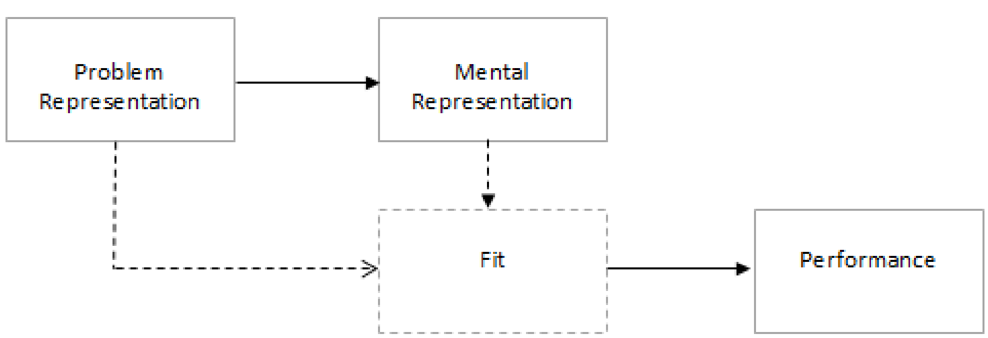
Subsequent research recognized the need to differentiate between two types of representations of the problem domain - internal and external representation (Shaft & Vessey, 2006). This resulted in the extended CFT which posits that superior problem solving performance requires a cognitive fit between the mental model of the problem, mental model of the solution and the external representation of the problem for a given task (See Figure 6).

Figure 6: Expanded CFT (Shaft and Vessey, 2006)



More recently, based on CFT, another theoretical contribution has been suggested – alternative fit (Chan, Goswami, & Kim, 2012). Given the idea of the formation of mental representation in CFT, Chan et al. (2012) propose an alternative mechanism of cognitive fit between different problem representations and their corresponding mental representations under condition of fixed task and varied problem representation. They tested the theory in spreadsheet context but given the novelty of their contribution no other empirical support is available at the moment.

Figure 7: CFT - Alternative Fit



2.2.2 Cognitive Fit-based Empirical Literature

After the introduction of CFT, the theory quickly became adopted across disciplines and contexts. To the best of my knowledge Table 4 provides the most current and the most comprehensive summary of empirical research that is theoretically based on any one of the versions of CFT discussed in previous section. The list of included literature was a result of extensive literature search using 'Cognitive Fit' and 'Cognitive Fit Theory' as keywords using Business Source Complete database. The search query also excluded any articles published prior to 1991 (year of CFT publication). Since I was interested in empirical support of CFT-established relationships, the original list was trimmed down to include only empirical research. The list of references used in the remaining literature was consulted to identify any empirical research that might have been missed in the original keyword search. The final list of 28 articles remained and was classified by discipline, problem domain, key theoretical elements (task, presentation), dependent variable, subjective assessment of the level of CFT support, and articles key contribution.

Available research shows that CFT has been adopted across great number of domains. CFT has been empirically tested in domains such as personal and firm level finance (Frownfelter-Lohrke, 1998; Umanath & Vessey, 1994; Urbaczewski & Koivisto, 2008), accounting (Cardinaels, 2008; Dunn & Grabski, 2001), human resources (Tuttle & Kershaw, 1998), modeling (Agarwal, Sinha, & Tanniru, 1996; Khatri, Vessey, Ramesh, Clay, & Park, 2006), software and programming (Shaft & Vessey, 2006; Umanath & Vessey, 1994), geographic systems (Dennis & Carte, 1998; Joshi et al., 2012; Mennecke, Crossland, & Killingsworth, 2000) , language and motor skills (Beckman, 2002; Hubona, Everett, Marsh, & Wauchope, 1998), operations and production (Speier, 2006; Teets, Tegarden, & Russell, 2010), mobile devices (Adipat et al., 2011; Urbaczewski & Koivisto, 2008) , online environments and virtual reality (Hong, Thong, & Kar Yan, 2004; Suh & Lee, 2005), healthcare (Joshi et al., 2012), sales and channel preference (Brunelle, 2009), and software tools (Chan et al., 2012; Goswami, Chan, & Kim, 2008).

The summary table shows that although each study had its individual contribution, there are a number of common themes that emerge from CFT – based literature. First, decision performance is largely focused on performance quality as measured though efficiency (time) and effectiveness (accuracy). Only a handful of studies introduced also evaluate performance though alternative dependent variables such as beliefs and attitudes (confidence (Goswami et al., 2008), ease of use and usefulness (Adipat et al., 2011) , purchase intentions (Kamis, Koufaris, & Stern, 2008; Suh & Lee, 2005)), choice preference (Brunelle, 2009), and learning curve (Frownfelter-Lohrke, 1998). Second, all studies but one treated cognitive fit as an emergent property of exogenous independent variables (task, problem representation, mental representation, skills, etc...). In one single instance (Brunelle, 2009), cognitive fit was considered as moderating emergent property. Third, cognitive effort was used as mechanism that regulates the impact of cognitive fit or lack thereof on decision performance in every single study; however, none of the studies actually attempted to (i) measure it in such capacity and (ii) validated its impact on performance. Fourth, while the largest number of studies considered tables and graphs as external representation formats, the nature of external representation formats has moved away from standard BIV presentation formats therefore distancing itself somewhat from the original presentation format used by the original theory. Some of the new problem representations considered within the emergent concept of Cognitive Fit includes modeling tools (Agarwal et al., 1996; Khatri et al., 2006), maps and route directions (Dennis & Carte, 1998; Hubona et al., 1998), programming languages (Sinha & Vessey, 1992), product nature (Suh & Lee, 2005), gaming tools (Beckman, 2002), online interface designs (Adipat et al., 2011; Kamis et al., 2008) and sales channels (Brunelle, 2009). Fifth and directly linked to previous point, the list and diversity of domains and contexts used by empirical research using CFT continues to grow. Table 3 shows that interest in CFT continues to grow as the number of empirical research articles appears to steadily grow.

	Years: 1991 - 2012					
5 year groupings	1991 - 1995	1996 - 2000	2001 - 2005	2005 - 2010	2011 – 2012(*)	1991 - 2012
Article count	3	7	5	9	4	28
(*) partial grouping –only 2 years						

Table 3: CFT-based Empirical Research Trend

Author (Year)	Domain	Task	Data Representation	Dependent Variable	CFT Support	Contribution
Vessey and Galletta (1991)	Bank account management	Spatial vs. Symbolic	Graphs vs. Tables	Time and Accuracy	**Partial support** of CFT (no support for the accuracy performance for spatial tasks)	Suggestions are made for extending the notion of fit to more complex problem-solving environments
Sinha and Vessey (1992)	Programming languages	Recursive vs. iterative	LISP vs. PASCAL		**Partial support** of CFT Cognitive fit effects were found for LISP programmers but not PASCAL programmers	First extension beyond Graph/Table data representation.
Umanath and Vessey (1994)	Bankruptcy predictions	Low information load vs. High information load prediction (holistic task)	Schematic faces vs. Graphs vs. Tables	Time and Accuracy	**Support** of CFT: Graphs outperform tables and schematic faces for multiattribute judgment tasks.	First to extend CFT and use graphs to present multiattribute data. Cognition is essential in supporting decision making. Suggestion of users resorting to strategy change to reduce cognitive effort – requiring process tracing methods.
Agarwal et al. (1996)	Requirement modeling	Process oriented vs. Object oriented	Process modeling tools vs. Object modeling tools	Solution quality	**Partial support** of CFT (no support for the quality performance for object focused task/tool)	Extends CFT to system analysis and design
Smelcer and Carmel (1997)	Geographic Information Systems	Low vs Medium vs High difficulty	Tables vs Maps	Time	**Support** of CFT: Maps outperform tables under conditions of geographic relationship (proximity, adjacency and containment)	First to extend CFT to Maps. Found that the impact of fit increases with the increase in task difficulty.
Dennis and Carte (1998)	Geographic Information Systems	Geographic containment vs. Geographic adjacency	Map vs. Table	Decision Process, Time and Accuracy	**Support of CFT** for adjacency **Contradicts CFT** for decision accuracy for containment/maps	Extends CFT to geographic tasks. CFT is applicable to GIS in terms of information presentation driving decision process but is not applicable to multicue, complex geographic tasks.

Author (Year)	Domain	Task	Data Representation	Dependent Variable	CFT Support	Contribution
Frownfelter-Lohrke (1998)	Firm financial condition predictions using financial statements	Spatial vs. Symbolic	Graphs vs. Tables vs. Hybrid	Learning curve, Decision Time and Accuracy	**Does not support** CFT	Empirical questioning of the CFT
Hubona et al. (1998)	Computer-displayed, language-conveyed spatial information	Route-formatted based inference vs. Survey-formatted based inference	Route oriented textual description vs. Survey oriented textual descriptions	Time and Accuracy	**Partial support** of CFT: 1) Fit between format and task partial 2) Fit between skill and task and format partial 3) Fit between skills and format - partial	Extends CFT to natural language. Study underscores the importance of cognitive skills for problem-solving performance.
Tuttle and Kershaw (1998)	Employee performance evaluations	Analytic (Symbolic) vs. Holistic (Spatial)	Graphs vs. Tables	Time and Accuracy (consistency, model quality)	**Supports** CFT	Extends CFT to judgment strategy by providing evidence that matching the information presentation to the strategy improved judgment performance.
Mennecke et al. (2000)	Spatial Decision Support Systems – maps	Single-cue spatial vs. Multi-cue complex spatial	SDSS vs. Paper maps	Time and Accuracy	**Partial support** of CFT: professionals who used the SDSS were no more accurate than professionals using paper maps	Extends CFT to SDSS. Suggestion offered that individual characteristic such as different types of knowledge should be added to CFT. Technology (format) suggested as potential 'equalizer' to novices.
Dunn and Grabski (2001)	Accounting models	Moderate localization vs. Strong localization vs. No localization	Debit-Credit-Account vs. Resource-Event-Agent models	Time, Accuracy, Ease of use, Usefulness	**Partial support** of CFT: No support for time, confidence and ease of use	Suggest that localization may be important part of cognitive fit. Formats that enable localization may eliminate the effect of experience.
Beckman (2002)	Human performance on motor tasks	Three motor tasks	M1 tank simulator vs. joystick	Time and Performance	**Partial support** of CFT: two tasks supported CFT, two tasks had inconclusive results	Extends CFT to human motor task performance
Speier et al. (2003)	Interruptions	Spatial-simple, spatial-complex, symbolic-simple, and symbolic-	Graphs vs. Tables	Time and Accuracy	**Supports** CFT: the matching of presentation format to task type is validated even in cases of	First study to test CFT to complex tasks. Evaluate the influence of interruptions on different

Author (Year)	Domain	Task	Data Representation	Dependent Variable	CFT Support	Contribution
		complex task			complex tasks	types of decision-making tasks and the ability of information presentation formats to alleviate them.
Hong et al. (2004)	Online shopping	Searching vs. Browsing	Matrix vs. List format	Time and Recall	**Partial Support** of CFT: support performance but not effort implications of CFT	Extends CFT to interface design of e-commerce websites
(Suh & Lee, 2005)	Virtual reality in B2C context	N/A – focus not on task but rather product experience (Direct vs. Indirect vs. Virtual)	Virtually high experiential and virtually low experiential products	Knowledge, Purchase intentions, Attitude	**Supports** CFT: the effects of VR are more pronounced when it exhibits products whose salient attributes are completely apparent through visual and auditory cues	CFT provides a foundation for relations between different product types and Virtual Reality
Khatri et al. (2006)	Conceptual modeling	Syntactic comprehension task vs. Semantic comprehension task vs. Schema-based problem-solving task	ER vs. EER modeling	Decision Accuracy	**Supports** CFT	Extends CFT to describe the role that application domain knowledge plays in solving different types of conceptual schema understanding tasks
Shaft and Vessey (2006)	Software maintenance	Function vs. Control flow software modification	Accounting vs. Hydrology COBOL program	Modification performance quality	**Supports** CFT: Study found that cognitive fit moderates the relationship between comprehension and modification	Extended original CFT to include Internal Representation
Speier (2006)	Operations Management	Spatial-simple, spatial-complex, symbolic-simple, and symbolic-complex	Graphs vs. Tables	Time and Accuracy	**Partial Support** of CFT: supports for simple task but contradicts for complex spatial tasks	Evaluates CFT in complex task environment and provides a suggestion for more nuanced approach to task complexity
Cardinaels (2008)	Accounting - Activity Based Costing	Complex accounting task	Graphs vs. Tables	Decision Quality (Profitability)	Study did note evaluate results through CFT lens	Provides empirical support of interaction between presentation format and domain knowledge
Goswami et al. (2008)	Spreadsheets	Correcting Link and Non-link Errors	Excel spreadsheet without a visualization tool	Time and Confidence	**Partial support** of CFT: Fit leads to better performance but does not	Extends CFT to spreadsheet error correction and suggests

Author (Year)	Domain	Task	Data Representation	Dependent Variable	CFT Support	Contribution
			and Excel spreadsheet with a visualization tool		impact confidence	that better performance can result when there is cognitive fit between the visualization tool and the error correction task.
Kamis et al. (2008)	Online customer DSS	Product customization	Attribute-based vs. Alternative-based interface design	Intention to purchase and Intention to return	**Support** of CFT: Perceived usefulness and Perceived enjoyment can fully mediate the impact of cognitive fit on the user's behavioral intentions.	Study first to integrate decision process variables, such as user beliefs and attitudes with the notion of cognitive fit
Urbaczewski and Koivisto (2008)	Mobile device (Bank account management)	Spatial vs. Symbolic	Graphs vs. Tables	Time and Accuracy	**Partial Support** CFT : does not support the accuracy performance for spatial tasks	Extends cognitive fit theory to mobile devices. Research replicated on a mobile device the original Vessey and Galletta [1991] and found approximately the same results. Noted that in mobile tasks CFT not as important as other human-computer interaction concepts.
Brunelle (2009)	Commercial context (consumer channel preference)	Scenarios of - Spatial and symbolic information search	Bricks-and-mortar vs. Online store	Consumer channel preference level	**Mainly Supports** CFT	Extends CFT to commercial context - consumer channel preference. Also, first use of 'cognitive fit' as a moderating variable between 6 IV and channel preference (DV)
Teets et al. (2010)	Production - quality assurance	Detection of quality problems – varying degree of process complexity and types of quality issues	2D Graphs, 3D Graphs vs Tables	Time and Accuracy	**Partial support** of CFT (does not support the accuracy performance for spatial tasks)	Extends CFT to more nuanced view of task complexity while integrating the proximity compatibility principle in assessing both 2D and 3D visualizations
Adipat et al. (2011)	Mobile device (search tasks)	High (across-document	Presentation adaptations: No	Time, accuracy, perceived ease of	**Supports** CFT	Indication that the cognitive fit theory could

Author (Year)	Domain	Task	Data Representation	Dependent Variable	CFT Support	Contribution
		browsing) vs. Low Complexity (within-document browsing)	adaptation, tree-view, tree view with hierarchical text summarization, tree view with visualization, tree view with hierarchical text summarization and with visualization.	use, perceived usefulness		be well extended to the mobile Web context
Chan et al. (2012)	Spreadsheets	Visual spatial task: find precedent cell in a spreadsheet.	A1 problem presentation vs. C1R1 problem presentation	Time and Accuracy (error)	**Supports** CFT	Alternative fit was assessed (fit between mental representation and information content) and empirically validated to lead to quicker judgments with fewer errors.
Shen, Carswell, Santhanam, and Bailey (2012)	Emergency Management Information Systems	Horizontal vs. Vertical vs. Combine information tasks	Plan view vs. Elevation view vs. 3D Display	Time, Accuracy and Workload	**General support of CFT**-based fit.	Decision guidance may impact the preference for format and decision making performance. First to evaluate roles of decision guidance and adaptable 2D/3D displays in crisis and other decisional situations

Table 4: Empirical CFT-based Literature Overview

The analysis of CFT-based empirical literature also shows evidence of interest in attempting to use CFT implications in more complex tasks however, the majority of literature either does not directly consider task complexity or even when it does, it keeps task and task complexity constant in the experimental design. Similarly, research is showing great diversity and, to some degree, lack of task classification uniformity. Given the importance of task in CFT, next section will discuss and present various task classifications so that it may inform and guide the research model.

2.2.3 Cognitive Fit and Task

Considerable agreement exists that the characteristics of the task in which an individual is involved is a prime determinant and a moderator of decision making performance (Frownfelter-Lohrke, 1998). IS discipline adopted this view of task in a number of seminal research efforts. Mason and Mitroff (1973) offered one of the first IS frameworks focused on decision making in which they recognized the importance of presentation format. In addition to organizational context and method of analysis components of the framework, they proposed that the type of task or decision activity performed and user characteristics need to be considered as well. Similarly, Task Technology Fit (TTF) theory holds that IT is more likely to have a positive impact on individual performance and be used if the capabilities of the IT match the tasks that the user must perform (Goodhue & Thompson, 1995).

Given the theoretical importance of task it might be appropriate to situate tasks into larger discussion of task types. There appears to be a number of classification schemes that separates tasks into categories. Decision science literature analyzes tasks by the level of mental processing required to complete the task (Jarvenpaa & Dickson, 1988; Kumar & Benbasat, 2004) . Cognitive Fit Theory-based research primarily classifies tasks through alignment with information representation (Vessey, 1991a). There are a number of other classification criteria; task understandability (Lim & Benbasat, 2000), dimensional integrity (Amer, 1991), alignment with decision making processes (Hard & Vanecek, 1991), task complexity , task structure and task content (Dickson, DeSanctis, & McBride, 1986). Table 5 provides a brief summary of classification criteria, task type, and task examples.

Regardless of the classification criteria, the role of task is generally accepted as important in users' ability to achieve cognitive fit. Although extant literature discusses the importance of task and its fit with presentation format (Vessey, 1991a), the findings are not conclusive, particularly for more complex tasks (Frownfelter-Lohrke, 1998; Speier, 2006; Speier et al., 2003). Given that for decision making context often deployed in DSS and BI, tabular vs. graphical presentation is most relevant, the cognition task type (spatial vs. symbolic) is appropriate to evaluate cognitive fit. Similarly, given inconclusive results relative to CFT effects on complex tasks, it would be particularly insightful to simultaneously consider task complexity. Therefore, task classification involving the combination of two task types (simple-symbolic, simple-spatial, complex-symbolic, and complex-spatial) adopted by (Speier, 2006) is the most relevant to this research.

Criteria	Task Type	Task Examples	Author(s)
Mental Processing	Elementary Tasks	Summarizing data, Showing trends, Comparing points and patterns, Showing deviations, Point/value reading	(Jarvenpaa & Dickson, 1988; Kumar & Benbasat, 2004)
	Higher Mental Tasks	Problem finding, Comprehension of information, Performance review, Forecasting, Exception reporting, Planning or allocation of resources, and Exploratory data analysis	
Cognition	Spatial	Determining relationship, Making comparisons, Interpolating	(Vessey, 1991a)
	Symbolic	Determining values	
Integration	Simple tasks	Determining project status	(Liberatore, Titus, & Dixon, 1988)
	Range tasks	Probe the size of the variance	
	Integrated tasks	Interpreting information contained in two consecutive displays	
Understanding	Analyzable tasks	There is common understanding of what is needed to perform the task	(Lim & Benbasat, 2000)
	Less-Analyzable tasks	Lack of predefined knowledge of what is needed to solve the problem	
Decision/Selection	Judgment	Making decision about a number of alternatives in a set	(Einhorn & Hogarth, 1981a)
	Choice	Selection of preferred alternative	
Decision-making processes	Accumulation	Acquiring and recalling a single information cue	(Hard & Vanecek, 1991)
	Recognition	Recognizing patterns or relationships between two or three information cues	
	Estimation	Identifying trends between numerous information cues	
	Projection	Making projections of future values	
Attention localization	Strong	Strong "drawing" of attention to relevant relationship	(Dunn & Grabski, 2001)
	Moderate	Attention salient mechanism is less present	
	Low/None	Lacks "drawing" of attention to relevant relationship -	
Complexity	Low	Small number of variable to consider	(Dickson et al., 1986)
	High	Large number of variables to consider	
Structure	Low	Absence of explicit steps/procedure	
	High	Set-by-step procedures	
Content	Low	Familiar task	
	High	Non-familiar task	
Cognitive process	Holistic	Task requiring assessment of information as a whole	(Umanath & Vessey, 1994)
	Perceptual	Task requiring visual comparisons	
	Analytical	Task requiring a reference to a single data point	
Complexity-Representation	Simple-symbolic	Small number of variables to consider in determining values	(Speier, 2006)
	Simple- spatial	Small number of variables to consider in determining relationship	
	Complex-symbolic	Large number of variables to consider in determining values	
	Complex-spatial	Large number of variables to consider in determining relationship	

Table 5: Task Classification Overview

2.2.4 Cognitive Fit Literature – Identified Gap

Preceding paragraphs and Table 3 and Table 4 provided both chronological and domain focused analysis of available empirical CFT research. Furthermore, the reviewed literature provided key contributions and understanding of tasks, problem representations and other variables as we attempt to understand the state of the knowledge on the role of cognitive fit on decision performance.

From empirical perspective, the focus of available data representation-decision performance research continues to explore mostly task characteristics and to some degree individual characteristics such as visual and cognitive skills (Hubona et al., 1998), domain knowledge and experience (Cardinaels, 2008; Dunn & Grabski, 2001; Khatri et al., 2006; Mennecke et al., 2000; Shaft & Vessey, 2006), and mental and schema representation (Chan et al., 2012; Khatri et al., 2006; Shaft & Vessey, 2006) as well as system characteristics (Goswami et al., 2008; Hubona et al., 1998). There is a solid body of evidence that suggest that the above empirical focus is appropriate. On the other hand, the literature shows growing list of studies with findings the either partially support or contradict CFT implications (See Table 4). Furthermore, faced with inconclusive results and despite the criticality of data representation, academic IS research failed to actually (i) measure the impact of data representation on cognitive effort and (ii) assess the impact of users' cognitive effort on decision making efficiency and effectiveness. Given the significant theoretical role of users' cognition effort in data representation literature, the lack of more nuanced and empirical support for that notion represents a major shortcoming and offers potential to clarify some of research and practical dilemmas. As a result, in this research I suggest that by adopting direct recognition of cognitive effort I am addressing important and essential missing element in the current literature that has not moved beyond existing inconclusive results.

Research question focused on understanding and better measurement of the implications of representation design on users' cognitive effort would extend our current knowledge in BIV as an important component of BI/DSS and decision making process. As business users depend on data for informed decision making, this data is packaged and presented to them visually; therefore, the understanding of the role of business information visualization on cognitive effort and decision performance offers potential to contribute a new stream of research, while allowing practitioners to learn and implement best practices centered on enabling desired effect of visualization on users' cognitive effort.

Given the identified importance of cognition highlighted in the overview of Business Information Visualization literature, as well as the importance of cognitive effort in resulting Cognitive Fit literature, in the next section I turn my attention on evaluation key findings from Cognitive Psychology and HCI literature as it relates to cognitive effort and its measurement.

2.3 Cognitive Effort

2.3.1 Cognitive Psychology and Decision Making Perspective

Cognitive effort has been defined as the total amount of cognitive resources needed to complete a task and it includes cognitive resources of perception, memory and judgment (Cooper-Martin, 1994; Russo & Dosher, 1983). Cognitive effort research originates as a theoretical construct in cognitive psychology (Johnson & Payne, 1985; Kahneman, 1973; Navon & Gopher, 1979; Norman & Bobrow, 1975; Thomas, 1983) whose impact on human performance is widely recognized.

Even prior to these studies one can see the understanding of the effort as factor in performance that can be evaluated through various lenses such as a response, capacity, motivation, and attention. For example, Logan (1960) assumes that effort is disincentive to a response (performance) in a study of incentive motivation in rats. Similarly, in the theory of achievement motivation Atkinson (1957) equated motivation with effort. Kahneman (1973), on the other hand, equates effort with cognitive capacity available when a person is engaged in a task and suggests that it fluctuates in response to the varying demands of the task. In Kahneman's theory, it is assumed that effort is reflected by some index of arousal, such as pupillary dilation. Norman and Bobrow (1975) approached the discussion by suggesting that various forms of cognition such as memory, processing effort and communication channels are resources and as such are always limited and finite. When processes occur concurrently, finite resource such as cognitive effort must be allocated across those processes. Furthermore, they differentiated between data-limited and resource-limited processing efforts. Navon and Gopher (1979) build on the idea single pool of resources by suggesting that the human-processing system incorporates a number of mechanisms, each having its own capacity.

In addition to extensive research on cognitive effort within cognitive psychology, particularly relevant to this study is the literature focused on the role of cognitive effort in decision making. According to the large body of research, decision makers are influenced by the goal of minimizing cognitive effort (Bettman, Johnson, & Payne, 1990; Cooper-Martin, 1994; Johnson & Payne, 1985). Just as it has been noted in consumer research that consumers may avoid particular choice selection process because it requires a significant effort and opt to select to use an easier process instead (Cooper-Martin, 1994), a decision maker may avoid a complex decision making process and in favor of an easier one. This preference for cognitive effort minimization may result in suboptimal decisions. Given this preference for minimization of cognitive effort, it would be very valuable to understand how a system can support lowering of cognitive effort while maintain or even improving decision performance.

2.3.3 Phenomenon Measurement

Cognitive effort has been measured through a number of methods and dimensions. One of the earlier methods called 'the cost of thinking' was introduced by Shugan (1980). This methodology suggests that the cost of thinking, as an indicator of cognitive effort, consists of comparing alternatives across an attribute. This method prescribes to a view that cognitive effort should be measured by dividing a choice process into components (Cooper-Martin, 1994). In similar fashion Johnson and Payne (1985) used Elementary Information Processes (EIPs). This system describes a heuristic as a sequence of mental events and has been found to provide good prediction of cognitive effort as it relates to response time and for subjective reports (Bettman et al., 1990).

In addition to this component ‘view’, existing research suggested that cognitive effort is a multidimensional concept (Gopher & Donchin, 1986) consisting of time, cognitive strain and total cognitive effort dimensions (Cooper-Martin, 1994). Time dimension has been defined as time period (duration) over which an individual expands cognitive effort and was used by Bettman et al. (1990) and Wright (1975) as self-reported, while Bettman et al. (1990) and Christensen-Szalanski (Christensen-Szalanski, 1978, 1980) as objective decision time. According to this measurement, the increase in duration (both self-reported and decision time) is equated with increase in cognitive effort (Table 6).

Measures of Time Dimension	Scale
1. Decision Time	# of seconds form viewing to decision
2. I didn’t take a lot of time to choose solution	1(strongly disagree)– 7 (strongly agree)*

* Reverse coded

Table 6: Measuring Cognitive Effort – Time Dimension

(Adopted from Cooper-Martin (1994))

The second dimension of cognitive effort is cognitive strain. Past literature measured cognitive strain as a self-reported subjective measure (Cooper-Martin, 1994; Wright, 1975) using 1-7 scale (Table 7). In the analysis of three dimensions of cognitive effort Cooper- Martin (1994) used self-reported statements as measures of cognitive strain by adopting item questions from Wright (1975), as well as by adding an additional measure of cognitive strain labeled 'Statements on alternatives' using total number of statements (defined as complete thoughts) one uses within specified timeframe of choice/decision evaluation; the greater the number of statements on alternatives (for a given choice) the greater the cognitive strain.

Measures of Cognitive Strain Dimension	Scale
1. I was careful about which (coffee mug) I chose	1(strongly disagree) – 7 (strongly agree)
2. I thought very hard about which (coffee mug) to pick	1(strongly disagree) – 7 (strongly agree)
3. How much effort did you put into making this decision?	1(v. little effort) – 7 (great deal of effort)
4. I didn't pay much attention while making a choice	1(strongly disagree) – 7 (strongly agree)
5. I concentrated a lot while making this choice	1(strongly disagree) – 7 (strongly agree)
6. It was difficult for me to make this choice	1(strongly disagree) – 7 (strongly agree)
7. Statements on alternatives	Number of statements

* Reverse coded

Table 7: Measuring Cognitive Effort - Cognitive Strain Dimension

(Adopted from Cooper-Martin (1994))

The third dimension of cognitive effort has been labeled as 'total cognitive effort'. Previously mentioned method called 'the cost of thinking' (Shugan, 1980) suggested that comparisons and costs capture total cognitive effort. If a user made a statement about the choice, the number of *comparisons* in the statement would constitute a measure of cognitive effort (Cooper-Martin, 1994). Similarly, literature considered that the inclusion of certain variables captures the *cost* *element* to the effort and is positively related to cognitive effort: (i) # of attributes processed (Wright, 1975) (ii) # of alternatives processed (Wright, 1975), and (iii) number of comparisons processed (Shugan, 1980). Table 8 summaries the measures of comparisons and costs that have been used to capture total cognitive effort.

Measures of Total Cognitive Effort	Scale
1. Comparisons	# of comparisons within a statement
2. Multiple Processing	# of attribute/alternative references
3. Compensatory Processing	# of tradeoffs b/w good and bad attributes
4. Prior Standards	# of comparisons to acceptable standard
5. Number of Alternatives	# of alternatives examined

Table 8: Measuring Cognitive Effort – Total Effort Dimension

(Adopted from Cooper-Martin (1994))

Cooper-Martin (1994) reviewed the validity and reliability of the three dimensions of cognitive effort within consumer choice context and limited sample (using 14 measures reviewed above) and found that the model with all three dimension had best overall fit and even with some contradictory findings still suggest the need to view cognitive effort as multidimensional concept. Although majority measures showed convergent and predictive validity there were some concerns reported relative to reliability and discriminant validity. Most importantly, dimensions of strain and time lacked discriminant validity. In other words, within a single decision an increase in strain also resulted in an increase in time. Furthermore, because of lack of reliability in some cases, the study recommended only a portion of self-reported measures of cognitive strain and total effort be used (Table 9).

Dimension	Measure	Scale
1. Time	Decision Time	# of seconds form viewing to decision
2. Strain	I thought very hard about which to pick	1(strongly disagree)–7(strongly agree)
	I concentrated a lot while making this choice	1(strongly disagree)–7(strongly agree)
	It was difficult for me to make this choice	1(strongly disagree)–7(strongly agree)
	Statements on alternatives	Number of statements
3. Total Effort	Multiple Processing	# of attribute/alternative references

Table 9: Suggested Cognitive Effort Measures
(Adopted from Cooper-Martin (1994))

In addition to performance (time) and self-reported feedback- based evaluations of cognitive effort, a separate stream of research adopted the use of eye tracking technology to assess ones cognitive load when observing/evaluating a stimulus based on the notion that eye movements are cognitively controlled (Liu et al., 2010). The topic of eye movement behavior in visual tasks has a long history (Rayner, 1998a). The literature traditionally uses the concepts of cognitive load and cognitive effort interchangeably as the concept of cognition load has been captured though the measurement of cognitive effort. Furthermore, some have called it visual effort or the amount of effort needed in terms of eye movement to arrive at the answer (Sharif & Maletic, 2010). Direct link of visual effort to the cognitive fit has been theoretically supported by Sharif and Maletic (2010) through Just and Carpenter (1980) immediacy theory.

Regardless of the name, the eye tracking literature measured effort through eye gaze data of fixation, saccades and pattern. A fixation is the stabilization of the eye on an object on the stimulus and studies often count the number of fixations as it captures the number of times that users looks at information. Because fixations are indicators of users' attention and intense cognitive processing, they have been suggested as good indicators of cognitive effort (Djamasbi, Siegel, Skorinko, & Tullis, 2011).. Saccades are quick movements form fixation to fixation. Fixation pattern captures the area of a viewing object that receives fixation.

Eye-tracking studies have shown that cognitive load impacts eye movement (Djamasbi, Samani, & Mehta, 2012; Ikehara & Crosby, 2005; Rayner, 1998b). As suggested by Djamasbi et al. (2011) fixation count and pattern could be used as measures of the cognitive effort and that fixation area size difference is related differences in cognitive effort (Djamasbi et al., 2011). In their exploratory analysis of demanding online games (Djamasbi et al., 2012) show that fixation can predict both perceptions of the load as well as performance. A number of IS studies used eye tracking to measure cognitive effort (Bednarik, 2012; Buscher, Biedert, Heinesch, & Dengel, 2010; Djamasbi, 2007; Djamasbi & Loiacono, 2008; Djamasbi et al., 2012; Djamasbi et al., 2011; Djamasbi & Strong, 2008; Djamasbi, Strong, & Dishaw, 2010; Just & Carpenter, 1980; Kuo, Hsu, & Day, 2009; Sharif & Maletic, 2010). Table 10 lists representative eye tracking measures used in that literature.

Eye Tracking Cognitive Effort Measures	Definition
1. Fixation Count	# of eye fixations on the entire stimulus
2. Fixation Rate	# of eye fixations on particular area/# of eye fixations on entire stimulus
3. Avg. Fixation Duration	Average length of all fixations on the stimulus

4. Fixation Area	% of area covered by fixation

Table 10: Eye tracking measures of cognitive effort

In addition to web site usage and gaming, eye tracking has been used traditionally and successfully as a technique for measuring cognitive load in reading, psycholinguistics, writing, and language acquisition (Rayner, 1998b). Given the importance of cognition to effective presentation of business information, it is surprising that BI literature failed to consider the use of eye tracking in any meaningful way. This is a gap, and if successfully addressed, should be considered a significant for contribution to BI/DSS literature.

2.4 Need for Cognition

Studies focused on cognition and cognitive effort also suggest that individual and stable characteristic differences could impacts ones tendency to engage in activities requiring effort. Given the focus on cognitive effort, it is appropriate for this study to consider the role of a concept called Need for cognition.

Need for cognition (NFC) has been originally defined as a need to structure relevant situations in meaningful, integrated ways (Cohen, Stotland, & Wolfe, 1955). This study adopts definition by Cacioppo and Petty (1982) according to which NFC refers to stable individual differences in people's tendency to engage in and enjoy effortful cognitive activity.

Individuals' NFC is positively correlated with their level of education and ACT scores, as well as their high school and college grade point averages

(Cacioppo, Petty, Feinstein, & Jarvis, 1996), and has been shown to influence consumer behavior to a large degree. For example, high NFC consumers tend to be persuaded by the substance of a message, whereas consumers low in NFC are persuaded by incidental cues, such as the spokesperson delivering a message or the number of arguments presented (Petty et al., 1983). By mid-90s there were over a hundred NFC focused studies (Cacioppo et al., 1996) that mostly confirmed the validity of the concept. Over time, a list of 18 items emerged that effectively captures individuals' level of NFC (see Table 11 – from Cacioppo et al. 1996).

18-Item Need for Cognition Scale

Item Number	Item Wording
1	I would prefer complex to simple problems.
2	I like to have the responsibility of handling a situation that requires a lot of thinking.
3	Thinking is not my idea of fun.*
4	I would rather do something that requires little thought than something that is sure to challenge my thinking abilities.*
5	I try to anticipate and avoid situations where there is likely chance I will have to think in depth about something.*
6	I find satisfaction in deliberating hard and for long hours.
7	I only think as hard as I have to. *
8	I prefer to think about small, daily projects to long-term ones.*
9	I like tasks that require little thought once I've learned them.*
10	The idea of relying on thought to make my way to the top appeals to me.
11	I really enjoy a task that involves coming up with new solutions to problems.
12	Learning new ways to think doesn't excite me very much.*
13	I prefer my life to be filled with puzzles that I must solve.
14	The notion of thinking abstractly is appealing to me.
15	I would prefer a task that is intellectual, difficult, and important to one that is somewhat important but does not require much thought.
16	I feel relief rather than satisfaction after completing a task that required a lot of mental effort.*
17	It's enough for me that something gets the job done; I don't care how or why it works.*
18	I usually end up deliberating about issues even when they do not affect me personally.

* Reverse scoring is used on this item.

Table 11: Need for Cognition Scale

CHAPTER III

3. RESEARCH MODEL AND HYPOTHESES DEVELOPMENT

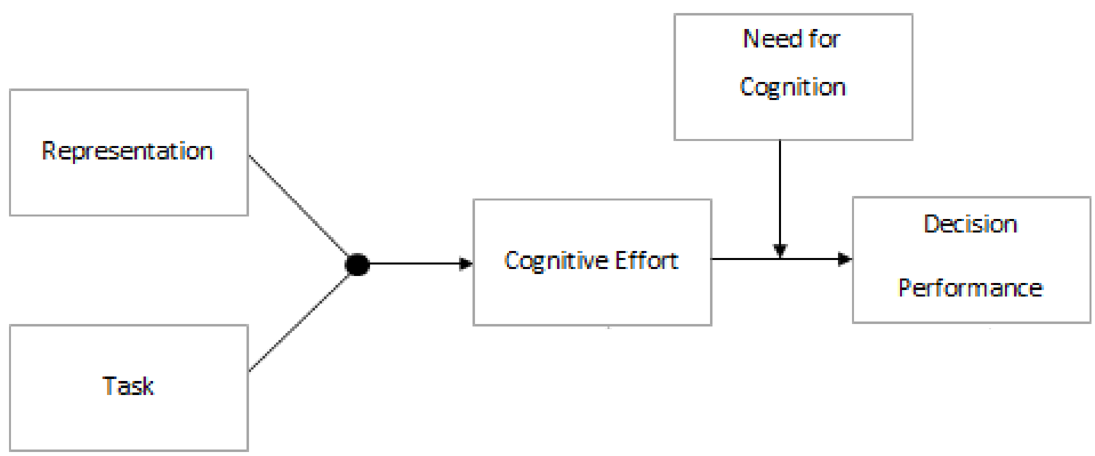
In Section II I provided extensive literature review with the goal of delivering key elements as building blocks to evaluate how data representation may interact with other variables to achieve desired effect on decision performance. Business Information Visualization literature provided the insight into and development of various presentation formats over time. It also situated tabular vs. graphical presentation literature and its impact on providing evidence that cognition and cognitive effort are significant elements to presentation effectiveness. Given the ubiquity of tabular and graphical formats in DSS and BI technologies it is appropriate to adopt them as two factors of data representation.

Cognitive Fit literature informed this research about the importance of cognitive fit, its elements and gaps, namely exclusion of direct measurement and cognitive effort construct integration in CFT-based models. Furthermore, it specifically called out for recognition of task appropriateness when dealing with tables and graphs, namely highlighting the importance of task complexity and informational representation (spatial vs. symbolic). Cognitive Effort literatures supplied available knowledge around the concept and provided strong case for its inclusion into any model that claims to explore decision performance. Lastly, given potential that the knowledge of domain in which task is contextualized may impact effort and decision performance, this research is assessed and accounted for this potential impact.

As a result, representation (table vs. graphs), task (simple-spatial, simple-symbolic, complex-spatial, complex-symbolic), cognitive effort and need cognition along with decision performance (time and accuracy) are included in the research model.

3.1 Model

Figure 8: Research Model



3.2 Variable Definitions

Data Representation – Information presentation format used to disseminate information to users (Kelton et al., 2010).

In developing task complexity type, this research adopts Wood (1986) view on Complex Task - task complexity is: (1) a function of the number of distinct information cues that must be processed; (2) the number of distinct processes that must be executed; and (3) the relationship (i.e., interdependence and change over time) between the cues and processes (Wood, 1986). Based on this definition as prior task definitions adopted by Speier (2006) that used representation/cognition based task classification from Vessey (1991), the following four task definitions are used:

- *Complex-symbolic tasks* - tasks that require symbolic information acquisition and evaluation subtasks that involve a large number of information cues, processes and inter-relatedness within the task (Wood, 1986).
- *Complex-spatial tasks* - tasks that require spatial information acquisition and evaluation subtasks and have *higher* levels of the complexity characteristics (Wood, 1986).
- *Simple-symbolic tasks* - tasks that require symbolic information acquisition and evaluation subtasks that involve a *low* number of information cues, processes and inter-relatedness within the task (Wood, 1986).

- *Simple-spatial tasks* - tasks that require spatial information acquisition and evaluation subtasks and have *lower* levels of the complexity characteristics (Wood, 1986).

Cognitive effort - The total amount of cognitive resources needed to complete a task and it includes cognitive resources of perception, memory and judgment (Cooper-Martin, 1994; Russo & Dosher, 1983).

Need for Cognition – stable individual differences in people's tendency to engage in and enjoy effortful cognitive activity (Cacioppo & Petty, 1982).

Decision Performance – measured as time (efficiency) and accuracy (effectiveness).

3.3 Hypotheses development

3.3.1 Representation-Task Fit and Cognitive Effort

Even some of the early research on graphical experiments concluded that the effectiveness of an information presentation is highly dependent on the task being performed (Benbasat et al., 1986b). Jarvenpaa and Dickson (1988) summarize early graphical presentation research as 'task motivated behavioral research' according to which the research on the efficacy of graphic formats 'can only be a matrix of *task environments* by presentation formats, with a set of contingencies based on user characteristics (p.766)'.

The role of task has been recognized not only in experiments but suggested in theoretical explanation of information presentation format's impact on decision making. The theory of cognitive fit (Vessey, 1991a; Vessey, 1991b, 1994) suggests that the efficiency and effectiveness of the problem solution depends on a fit between the problem representation and *the problem-solving task* (Kelton et al., 2010). According to CFT, task can impact cognitive effort as cognitive fit requires decision makers to either modify information presentation to better match *the task* or transform their decision processes to better match information presentation.

This paper suggests that, according to Cognitive Fit Theory, if external problem representation does not match to that emphasized in the task, there is nothing to guide the decision maker in working toward task solution, and they must exert *greater cognitive effort* to transform the information into a form suitable for solving that particular type of problem (Vessey, 1994). Therefore, this paper suggests the need to introduce cognitive effort as a mediating variable between representation-task fit and decision performance. Cognitive science literature and Cognitive Fit Theory provide the underlying mechanism for the link between data representation methods and elements with cognitive effort. Cognitive science established the appropriateness and the need to evaluate information visualization within the context of human cognitive elements of memory, mental models and internal representations. Cognitive Fit Theory, on the other hand, provides a link between cognitive fit and cognitive effort. Since data representation is a component of cognitive fit, one should expect a link between cognitive fit components with cognitive effort as well, hence:

H1: For Simple-symbolic tasks, symbolic (table) information presentation formats results in lower cognitive effort than spatial (graph) formats.

H2: For Simple-spatial tasks, spatial (graph) information presentation formats result in lower cognitive effort than symbolic (table) formats.

H3: For Complex-symbolic tasks, symbolic (table) information presentation formats result in lower cognitive effort than spatial (graph) formats.

H4: For Complex-spatial tasks, spatial (graph) information presentation formats result in lower cognitive effort than symbolic (table) formats..

3.3.2 Cognitive Effort and Decision Performance

Of particular interest to our understanding of cognition effort in decision making are the Cost-Benefit Principles and Relevance Theory. Cost-Benefit principles are rooted in the works by Beach and Mitchell (1978), Einhorn and Hogarth (1981b), Payne (1982), Russo and Dosher (1983), Johnson and Payne (1985), Bettman et al. (1990), Benbasat and Todd (1996). According to Cost-Benefit Principles, decision makers trade off the effort required to make a decision vis-a-vis the accuracy of the outcome. Relevance Theory, on the other hand, was introduced by Sperber and Wilson (1995) in which they suggest that the audience will search for meaning in any given communication situation and having found meaning that fits their expectation of relevance, will stop processing.

According to Cost-Benefit Principles decision makers are faced with a dilemma. They attempt to make accurate decisions (Johnson & Payne, 1985) where more effort is considered to lead to more accurate decisions (Klein & Yadav, 1989). On the other hand, decision makers are driven by their preference to minimize effort (Einhorn & Hogarth, 1981b) and are willing to forgo some of the decision accuracy in the process (Johnson & Payne, 1985). Given this tendency to optimize and subsequently reduce accuracy, data representation that reduces cognitive effort has a potential to attenuate the need to optimize. Therefore, using Cost-Benefit lens, I expect that the effect of data representation/task fit reduces cognitive effort which in turn lowers user's cost-benefit assessment of the need to optimize when compared to situation of lack of data representations/task fit. Alternatively, increase in the perception of cognitive effort caused by the lack of data representation/task fit amplifies user's cost-benefit assessment of the need to optimize resulting in a higher likelihood of settling for optimal cost-benefit assessment causing accuracy to suffer when compared to a scenario with data representation/task fit.

Relevance theory holds that the relevance of communication is determined by its cognitive effects and the effort needed to process them (White, 2011). In other words, the components could be expressed as ratio where *relevance = cognitive effects/processing effort* (Sperber & Wilson, 1996) where the greater the cognitive effects, the greater the relevance and the smaller the processing effort required to derive those effects, the greater the relevance.

Since RT principles apply not only to communication but also to cognition it could be evaluated in the context of decision performance and cognitive effort. Cognitive effect occurs when in input of newly presented information interacts with existing assumption either by strengthening, contradicting or by combining with it to reach a new conclusion (White, 2011). This understanding of cognitive effort fundamentally equates it with decision performance that also occurs when newly presented information interacts with data representation users' existing assumptions. Similarly, the relevance of communication can be equated to the effectiveness of decision process while processing effort can be equated to cognitive effort. Combined and applied to data representation context, RT states that the maximum effectiveness of decision process (relevancy) is achieved when data representation (newly presented information) enables one to achieve the optimal balance between decision performance (cognitive effect) and cognitive effort (processing effort). In other words, application of relevancy theory to cognitive effort induced by data representation/task fit suggests that appropriate representation for a task would yield the same cognitive effect for smaller processing effort, thus higher likelihood of relevance occurring faster (time) and with appropriate problem solution (accuracy) when compared to situations of higher cognitive effort being induced by lack of data representation/task fit.

Both Cost-Benefit Principles and Relevance Theory suggest that humans tend to be geared toward preference for minimizing cognitive effort while maximizing decision performance. Our ability to reduce cognitive effort for data representation users therefore may allow for users to reach decision performance that otherwise would not be attainable because that decision performance would require too great of a cognitive effect and thus be deemed suboptimal. This preference for optimal ratio between cost (effort) and benefit/effect (performance) leads me to suggest to negative impact of cognitive effort on decision performance.

However, this relationship is more nuanced as it needs to account for Need for Cognition literature that suggests for any given individual different situations will be differentially important for the arousal and satisfaction of the need. In addition, any given situation will have differential importance for the arousal and satisfaction of the cognition need (Cohen, Stotland, & Wolfe, 1955).

As defined by Cacioppo and Petty (1982) NFC refers to stable individual differences in people's tendency to engage in and enjoy effortful cognitive activity. Users high in NFC are intrinsically motivated to search for, gather, and analyze information in an effort to comprehend their world, devoting more cognitive resources to processing messages than consumers low in NFC. Furthermore, high NFC individuals intrinsically enjoy thinking and complex tasks, and are more likely to process information analytically (Haugtvedt, Petty, & Cacioppo, 1992). On the other hand, low NFC individuals tend to avoid effortful cognitive work, prefer tasks that require fewer cognitive resources, and are more likely to process information heuristically. Furthermore, prior study have found that NFC has moderating effect (Kim & Kramer, 2006; Zhang, 1996; Zhang & Buda, 1999)

Given the available literature on NFC, the relationship between cognitive effort and decision performance efficiency (time) underlined by users' optimization of cost-benefit/effort-accuracy is expected to be influenced by individuals' level of NFC. The expectation is that individuals willing to more engage in cognitive activity (higher NFC) will take longer to perform, therefore:

> **H5:** Increase in Cognitive effort increases the amount of time required for a decision and this relationship is amplified with increase in individual's Need for Cognition.

Similarly, the relationship between cognitive effort and decision performance effectiveness (accuracy) underlined by users' optimization of cost-benefit/effort-accuracy is expected to be influenced by individuals' level of NFC. The expectation is that for individuals with low NCF more effort will result in less accuracy as users will resort to optimization (to minimize the impact of higher effort) and therefore accuracy will suffer. On the other hand, individuals with higher NFC (willingness to engage) would less likely be engaged in optimization and their accuracy would not suffer as much with the increase in cognitive effort. For some it may even positively impact their accuracy, therefore:

H6: Increase in Cognitive effort decreases decision accuracy and this relationship is amplified with decrease in individual's Need for Cognition

3.4. Exploration

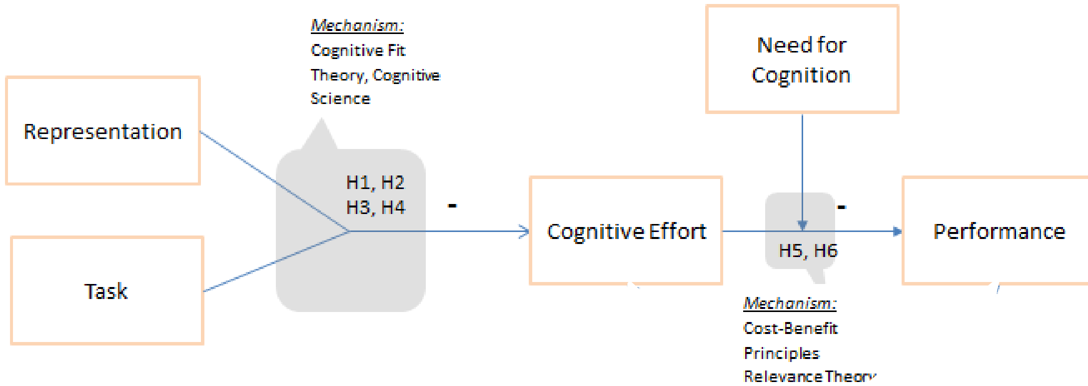
Although I am not in a position to formally hypothesize a particular role of NCF for complex tasks it needs to be noted that NCF might be able to explain some inconclusive results found in CFT-based empirical research when dealing with complex tasks.

In general, the research shows that the effectiveness and efficiency of a specific problem representation depends on characteristics of the task (Amer, 1991; Benbasat & Dexter, 1985, 1986; Benbasat et al., 1986a, b; Desanctis, 1984; Vessey, 1991a; Vessey, 1991b; Vessey & Galletta, 1991). While CFT created a concept to theoretically explain inconsistent results, the underlying issue of inconsistency of results in practice remains. A particular gap and inconsistency exists for complex task (Frownfelter-Lohrke, 1998). CFT was originally created as a theoretical framework attempting to address decision performance under elementary mental tasks that were mostly concerned with simple tasks requiring single operation on data (Speier, 2006). Given the reality of today's decision making and its complexity (Dennis & Carte, 1998), researchers recognized the value of and potential of applying CFT to complex tasks (Frownfelter-Lohrke, 1998; Speier, 2006; Vessey & Galletta, 1991). For example, Speier (2006) introduced task complexity into spatial vs. symbolic task paradigm resulting in four type of tasks: simple-symbolic, simple-spatial, complex-symbolic, and complex-spatial. The author found CFT-consistent results for simple tasks but some inconsistency for complex tasks and attempted to explain contradictory findings by suggesting a complexity framework based on complexity theory. This framework allows for segmentation of complex tasks by number of information acquisition and evaluation cues (Objective Task Complexity) and by Experienced Task Complexity. While offering a post-hoc analysis-based theoretical explanation of the problem no other attempt was made to validate the suggestion leaving us with inconclusive results. Given the potential for high NFC individuals to exhibit behavior contradictory to CFT, they may be particularly pronounced in more complex tasks.

3.5 Model Summary

Having established the mechanisms behind the relationships hypothesized by the Research Model, the final model with underlying mechanisms is identified.

Figure 9: Final Model



CHAPTER IV

4. METHODOLOGY

Two laboratory experiments supported by a pretest were conducted to investigate the propositions articulated in Section III and illustrated in Fig. 6. Study #1 used self-reported (perceptual) measure of cognitive effort to test the model. Study #2, in addition to self-reported measure of cognitive effort, leveraged eye-tracking technology and was primarily designed to capture physiological measures of cognitive effort. The following sections in Chapter IV will provide an overview of experimental designs of each study and define and operationalize variables.

4.1 Study #1

4.1.1 Experimental Design

Experimental design for study #1 consists of two parts. In the first portion of the study (H1 trough H4) a three-way between factor design experiment was deployed. In order to allow for analysis flexibility 4 literature-supported tasks – Simple-Spatial, Simple-Symbolic, Complex-Spatial, and Complex-Symbolic were achieved through Task Complexity (simple, complex) and Task Type (spatial, symbolic) factors and along with Representation factor (table, graph) constituted three independent factors. This resulted in 8 cell, 2 by 2 by 2 factorial design (See Table 14). Dependent variable for the first portion of the study was Cognitive Effort and it was measured as self-reported measure.

Expected Cognitive Fit Relationship between task and representation				
	Tasks			
	Simple		Complex	
Representation	Spatial	Symbolic	Spatial	Symbolic
Tabular	**Cell 1**	Cell 3	**Cell 5**	Cell 7
Graphical	Cell 2	**Cell 4**	Cell 6	**Cell 8**

Table 12: Study #1 - Experimental Design

This experimental design allows to evaluate the effect of representation – task fit as predicted by CFT that matches Spatial tasks (both simple and complex) to Graphical representation and Symbolic tasks (both simple and complex) to Tabular representation (see Table 14), where cells in **bold** represent theory predicted indication of cognitive fit while others represent the lack of cognitive fit.

In the second portion of the study, the interaction effect Cognitive effort and Need for Cognition was regressed against two dependent variables: Time (H5) and Accuracy (H6) to test the remaining two hypotheses. If support for H1-

H4 and H5 or H6 is found, evaluation of the mediation effect of cognitive effort * Need for Cognition will be evaluated.

4.1.2 Variables

Representation, Task and Need for Cognition are independent variables. For the purposes of testing H1 though H4, cognitive effort is a dependent variable. In tests of H5 and H6, cognitive effort serves a role of independent variable while decision performance measured of time (H5) and accuracy (H6) are dependent variables (Table 15).

Variables	Description	
Task	Simple-symbolic	See 4.1.2.1
	Simple-spatial	
	Complex-symbolic	
	Complex-spatial	
Representation	Table(s)	See 4.1.2.2
	Graph(s)	
Need for Cognition	Self-reported	18-item scale (See 4.2.3)
Cognitive Effort	Self-reported	6-item scale (See 4.2.4)
Time	Time to submit answer	See 4.2.5
Accuracy	Correctness of the choice/ judgment	

Table 13: Research Variables – Study #1

4.1.2.1 Tasks

Four tasks were used to conduct the study. In order to separate tasks into simple vs. complex, Wood's (1986) definition was used by creating two tasks that required low number of variables/information cues and calculations (simple) and two tasks that required high number of variables/information cues and calculations (complex). For both simple tasks existing CFT IS literature (Speier, 2006) tasks from Production Operations Management domain was adapted to a more generic Financial Accounting Domain.

In simple-spatial task subjects were asked to identify a month in which Actual Unit Rate is the highest for all three. This task required assessing the relationship between data point while trying to identify in which month is the unit rate the highest for combined locations. Using Wood's (1986) methodology for assessment of task, this simple-spatial task involved three information cues (Location, Month, Actual Unit Rate) for behavior act of addition across 6 months (with 6 products for subtask) and one information cue (Calculated unit rate) for behavior act of comparison relative to other 5 months (with 5 products for subtask). This task along with tabular representation format containing the necessary information to make a decision represented Cell 1, while the same task with graphical representation format represented Cell 2.

The simple-symbolic task required from subjects to obtain specific data by directly extracting information regarding unit rates for a specific location and a specific month. Once unit rates are located, they are subtracted from each other resulting in correct answer. Using Wood's (1986) methodology for assessment of task, the simple-symbolic task involved four information cues (Location, Month, Actual and Target Unit Rate), one behavior (calculate) with one product for a subtask (difference between two rates). This simple-symbolic task along with tabular representation format containing the necessary information to make a decision represented Cell 3, while the same task with graphical representation format represented Cell 4.

In the complex-spatial task, subjects were asked to use existing information for 6 firms to assess which companies meet both financial scenarios where each scenario had 3 and/or conditions. Using Wood's (1986) methodology for assessment of task, this complex-spatial task involved 17 information cues used in different ways on 9 different behavior acts of comparison (across 6 firms/12 months). The task required assessing the relationship between data points and it did not require precision, making it a spatial task as well. Tabular representation format containing the necessary information to make a decision for this task represented Cell 5, while the same task with graphical representation format represented Cell 6.

The complex-symbolic task consisted of a firm investment task based on the previously published operations management task (Buffa, 1990; Speier, 2006; Speier et al., 2003) adapted to financial accounting context. In the firm investment task, subjects were provided with five different balance sheet (liabilities) line items/categories associated with six firms. Subjects were asked to determine which firms to invest in. Using Wood's (1986) methodology for assessment of task involves 11 information cues ($ Amount, Firm, Accounts Payable, Accrued Expenses, Notes Payable, Bonds Payable, Total liabilities, Fixed amount of Total liabilities, Fixed % limit for Notes Payable, Fixed % limit for Accounts Payable) used in different ways on 4 different behavior acts of comparison (across 6 firms) and one behavior act of ordering. Given the number of the cues and behavioral acts this task is substantially more complex for the user when compared to two simple tasks. At the same time, the task is symbolic as it requires from subjects to obtain specific data by directly extracting information. This task along with tabular representation format containing the necessary information to make a decision represented Cell 7, while the same task with graphical representation format represented Cell 8.

4.1.2.2 Representation

Two types of information presentation formats were examined: tabular and graphical. The data used in this experiment was presented as a single or series of graphs and tables where subjects were exposed to each experimental task using either graph(s) or table(s). The aim of each representation is to supply sufficient information to subjects to correctly respond to each task. Previous research has been criticized for poor quality of representations and unequal level of data in those two formats. Special attention has been given to ensure and control that both representation formats have been designed using Information Visualization best practices in terms of layout, spacing, color, symbols and legend. Similarly, representation format design was deployed so that the granularity of data displayed is equivalent. Lastly, to better control the cognitive processes needed to acquire and interpret the information, all representations (and task problem statements) fit on one computer screen without the need to scroll or page down to see additional data.

In line with CFT literature, tabular representations were tables with firms/locations (selections) being placed vertically and attributes such as month, year, and various ratios horizontally. Two-dimensional bar charts and line charts were operationalized as the spatial format.

Each representation was exactly 1366 (width) by 768 (height) pixels in size in order to allow for optimal size given monitor size. This also ensured that any bias due to size of the representation is eliminated.

4.1.2.3. Need for Cognition

Existing literature uses 18 item scale to measure individual's level of Need for Cognition (Table 16). Cacioppo et al. (1996) provided extensive review of over 100 empirical studies of individual's tendency to engage in effortful activity, i.e. Need for Cognition. Table 17 represents abbreviated version of studies that used 18-point scale as reported by Cacioppo et al. (1996) along with an addition of representative sample of some more current research focused on NFC. Table provides description of subject characteristics (number, type, country), approach relative to # of scale items used, along with reported reliability measure (Chronbach α). Although table is by far not an exhaustive list of NFC studies with 18-item scale, it is a representative sample that clearly provides evidence that majority of studies using 18 item scale retain all items in their methodology. Furthermore, the only IS study that explored the role of NFC using CFT lens also used all 18 items (Mennecke et al., 2000).

NFC Item Wording
1 - I would prefer complex to simple problems
2 - I like to have the responsibility of handling a situation that requires a lot of thinking
3 -Thinking is not my idea of fun
4 -I would rather do something that requires little thought than something that is sure to challenge my thinking abilities
5 -I try to anticipate and avoid situations where there is likely chance I will have to think in depth about something
6 - I find satisfaction in deliberating hard and for long hours
7 - I only think as hard as I have to
8 - I prefer to think about small, daily projects to long-term ones
9 - I like tasks that require little thought once I've learned
10 -The idea of relying on thought to make my new way to the top appeals to me
11 -I really enjoy a task that involves coming up with new solutions to problems
12 - Learning new ways to think doesn’t excite me much
13 - I prefer my life to be filled with puzzles that I must solve.
14 - The notion of thinking abstractly is appealing to me.
15 - I would prefer a task that is intellectual, difficult, and important to one that is somewhat important but does not inquire much thought
16 -I feel relief rather than satisfaction after completing a task that required a lot of mental effort
17 - It’s enough for me that something gets the job done; I don’t care how or why it works
18 - I usually end up deliberating about issues even when they do not affect me personally.

Table 14: NFC 18-item scale

	Author	Subjects	County	items used	α
1	Cacioppo, Petty, and Chuan Feng (1984)	527/Students	USA	All 18 items	0.90
2	Spotts (1994) – Study 1	238/Adults	USA	17 out of 18	0.81
3	Spotts (1994) – Study 2	165/Adults	USA	17 out of 18	0.91
4	Berzonsky and Sullivan (1992)	163/ Students	USA	All 18 items	0.91
5	Furlong (1993)	61/Adults	USA	All 18 items	0.84
6	Kernis, Grannemann, and Barclay (1992)	95/Students	USA	All 18 items	0.87
7	Miller, Omens, and Delvadia (1991)	98/Students	USA	All 18 items	0.85
8	Peltier and Schibrowsky (1994)	130/Students	USA	All 18 items	0.97
9	Sadowski (1993)	1218/Students	USA	All 18 items	0.86
10	Sadowski and Gulgoz (1996)	51/Students	USA	All 18 items	n/r
11	Sadowski and Gulgox (1992) – Time 1	71/Students	USA	All 18 items	0.91
12	Sadowski and Gulgox (1992) – Time 2	71/Students	USA	All 18 items	0.92
13	Sadowski and Cogburn (1997)	85/Students	USA	All 18 items	n/r
14	Tidwell, Sadowski, and Pate (2000)	220/Students	USA	All 18 items	n/r
15	Venkatraman, Marlino, Kardes, and Sklar (1990)	77/Students	USA	All 18 items	0.83
16	Verplanken (1989)	2439/Adults	Holland	15 out of 18	0.85
17	Verplanken (1991)	2439/Adults	Holland	5 items	0.85
18	Verplanken (1993)	120/Adults+ Students	Holland	15 out of 18	0.80
19	Mussel, Goritz, and Hewig (2013)	1326/Adults	Germany	All 18 Items	0.87
20	Fleischhauer, Miller, Enge, and Albrecht (2014)	137/Students	Germany	16 out of 18	0.79
21	Dahui and Browne (2006) – Study 1	156/Students	US	All 18 items	0.80
22	Dahui and Browne (2006) – Study 2	127/Students	US	All 18 items	0.88
23	Mennecke et al. (2000)	240/ Adults+ Students	US	All 18 items	0.88

Table 15: Sample NFC Studies

Exception to that approach, and an accepted practice, occurs if an item exhibits unusually low inter-item correlations in which case the item is removed from subsequent analysis (Fleischhauer et al., 2014; Spotts, 1994; Verplanken, 1993). As a result and in line with existing literature, for pretesting purposes I included all 18 scale items.

Beyond establishing 18-item NFC scales as a thoroughly validated instrument, the review of NFC literature by Cacioppo et al. (1996) also suggests that NFC exhibits high level of reliability. Pretest found high Cronbach alpha (0.919) and average inter-item correlation of 0.338. In summary, 18 item scale used in pretest was in line with expectations and existing literature and was used in both study #1 and study #2 to measure NFC.

4.1.2.4 Cognitive Effort

Cognitive effort was measured both as a perceptual and physiological construct to enhance the contribution of the research. Study #1 was designed to focus on more traditional, subjects' perception of Cognitive Effort (self-reported) where it was to be measured via literature tested and validated preexisting scale items:

Measures of Cognitive Strain Dimension	Scale
1. I was careful about which answer I chose	1(strongly disagree) – 7 (strongly agree)
2. I thought very hard about which answer to pick	1(strongly disagree) – 7 (strongly agree)
3. I concentrated a lot while making this choice	1(v. little effort) – 7 (great deal of effort)
4. It was difficult for me to make this choice	1(strongly disagree) – 7 (strongly agree)

5. I didn't pay much attention while making a choice?	1(strongly disagree) – 7 (strongly agree)
6. How much effort did you put into making this decision?	1(v. little effort) – 7 (great deal of effort)

Table 16: Cognitive Effort (perception) Scale Items

Perception of time was not included as Time is a dependent variable in our model while elements such as number of statements and alternatives was not included as in the context of this study they are part of task complexity.

In order to ensure applicability of these scales to the context of the study, the scale was pretested for reliability and inter-item correlations. Cronbach's Alpha Based on Standardized Items for 6 items was 0.836 meeting the test (>0.7) of internal consistency with average inter-item correlation of 0.459. Pretest Cronbach's Alpha is in line with results reported by Cooper-Martin (1994) 0f 0.82. Both high internal consistency and inter-item correlation confirm appropriateness of the 6 item scale for this study and will be used in both studies.

Physiological measure of Cognitive Effort used in Study #2 was adopted from eye-tracking based literature where average fixation duration and fixation count have been used as a way to measure attention and cognitive effort (Table 17). Some have used fixation rate (# of eye fixations on particular area/# of eye fixations on entire stimulus) but given our context of single-screen presentation of both problem and solution data (table or graph) and where whole screen fixations are important the comparison of fixations on a portion of a screen to total screen in not as useful and therefore not included.

There is a debate and lack of agreement on fixation duration threshold in eye-tracking literature. This study adopts 200ms as a minimal duration threshold to be considered fixation, based on available research that suggests that most fixations are in 200-300ms duration range (Holmqvist et al., 2011).

Eye Tracking Cognitive Effort Measures	Definition
1. Fixation Count	# of eye fixations on the entire stimulus
2. Avg. Fixation Duration	Average length of all fixations on the stimulus

Table 17: Cognitive Effort (eye movement based) Measures

Although eye-tracking technology has been thoroughly validated in academia and practice for users attention and effort during viewing screen objects, small pretest with two users was conducted and successfully verbally confirmed that fixations (both duration and count) accurately presents users attention and effort during problem solving.

4.1.2.5 Decision Performance

Consistent with prior research evaluating the impact of representation on decision performance will be decision accuracy and decision time (Vessey, 1991a; Vessey & Galletta, 1991). To measure time survey tool used during experiment l captured start and end time for each task in seconds. The difference in start and end time was used to calculate total time. Based on pretest time the expectation was that 60 minutes will be sufficient time to complete the experiment. No artificial time limit was placed on subjects; however, all subjects completed the experiment in less than 45 minutes (average experiment time was 22 minutes)

In line with existing decision performance CFT-based literature, all tasks were intellective tasks (McGrath, 1984.) and as such, have optimal answers. To provide a standardized comparison across tasks, decision accuracy for each task was calculated as the percentage of optimal achieved (i.e., (1-(optimal solution-subject solution)/optimal solution))[1].

4.1.3 Subjects

Subjects were recruited from various business classes with both undergraduate and graduate students at Cleveland State University. Students received partial course credit for their participation. In order to further ensure subject motivation, participants were eligible to receive one of three $50 rewards for performance in terms of accuracy per unit of time.

4.1.4 Experiment Procedure and Set-up

Data collection for Study #1 occurred over two weeks in multiple sessions using Qualtrics online survey tool. All subjects completed the experiment in a large computer lab with investigator present. All subjects used the same equipment - a 19'' monitor connected to a desktop computer (Intel's Core 2 Duo processor and 2GB RAM) running Windows 7 Operating System.

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[1] In this research no hypothesized impact of Domain Knowledge is expected due to the nature of task. However, domain knowledge was measure as part of the survey in case it explains some difference in performance measures.

Standard process and script was followed for each session. The script consisted of brief investigator introduction and the explanation of the study. It was followed by explanation of procedures, risk/benefits, discomforts, compensation, and data confidentiality. Once subject was fully informed, consent form was signed and experiment initiated (See Informed Consent – Study #1 in Appendix).

Prior to data collection, 8 unique surveys were created and labeled survey 1 through survey 8. Surveys were identical except the portion that is focused on tasks for each experimental cell. Each survey included one simple-symbolic, one simple-spatial, one complex-symbolic and on complex-spatial task. They differed in the order in which tasks where presented and the format (graph/table) in which data was presented to solve the problem.

At the beginning of each experiment session user were randomly assigned a number between 1 and 8 and were provided a link to survey that matches their random number. Each survey collected subject's background information such as age, gender, class standing, major and years of work experience to describe the sample population of the study. The same survey was used to collect 18 items describing subjects' Need for Cognition. The order of NFC questions was randomized and the original wording was maintained where 9 out of 18 are reverse-worded. In each survey subjects were asked to solve 4 problems measuring their level of accounting knowledge. Last portion of the experiment survey consisted of 4 tasks associated with experimental cells. Online tool recorded time it took for each user to select answer(s) and captured multiple choice answers for each task. There was no time limit placed on the survey; however all subjects completed survey within 1 hour expected time.

Data was then exported from Qualtrics into a database. A series of queries was used to link and prepare data for import into SPSS statistical analysis tool for hypotheses testing and further analysis.

4.2 Study #2

4.2.1 Experimental Design

Unlike study #1, the first portion of the study #2 (H1 trough H4) experiment was a within-subject three factor design. The three independent variables were the same as in Study #1: Task Complexity (simple and complex), Task Type (spatial and symbolic), and Representation (table and graph). This resulted in 8 cell, 2 by 2 by 2 factorial design (See Table 18). Dependent variable for the first portion of the study was cognitive effort. In study #2, cognitive effort was measured both through eye-tracking (average fixation duration, fixation count) and as 6-item scale self-reported measure (as in study #1).

As in study #1, in the second portion of study #2, the interaction effect Cognitive effort and Need for Cognition was regressed against two dependent variables: Time (H5) and Accuracy (H6) to test the remaining two hypotheses. Unlike study #1, in this study it was repeated three times, once for each measure of cognitive effort. If support for H1-H4 and H5 or H6 was found, evaluation of the mediation effect of cognitive effort * Need for Cognition were to be evaluated

Expected Cognitive Fit Relationship between task and representation				
	Tasks			
	Simple		Complex	
Representation	Spatial	Symbolic	Spatial	Symbolic
Tabular	**Cell 1**	Cell 3	**Cell 5**	Cell 7
Graphical	Cell 2	**Cell 4**	Cell 6	**Cell 8**

Table 18: Study #2 Experimental Design

4.2.2 Variables

As in study #1, the independent variables are Representation, Task and Need for Cognition. Cognitive effort is a dependent variable for H1 – H4 and independent variable for H5 and H6. Decision performance as measured though time and accuracy is a dependent variable for H5 and H6.

Variables	Description	
Task	Simple-symbolic Simple-spatial Complex-symbolic Complex-spatial	See 4.2.2.1
Representation	Table(s) Graph(s)	See 4.2.2.2
Need for Cognition	Self-reported	18-item scale (See 4.2.2.3)
Cognitive Effort (CE_{SR})	Self-reported	6-item scale (See 4.2.2.4)

Cognitive Effort (CE_{FD})	Average Fixation Duration	(See 4.2.2.4)
Cognitive Effort (CE_{FC})	Fixation Count	(See 4.2.2.4)
Time	Time to submit answer	See 4.2.2.5
Accuracy	Correctness of the choice/ judgment	

Table 19: Research Variables - Study #2

4.2.2.1 Tasks

As in study #1, Wood's (1986) definition was used to create two tasks that required low number of variables/information cues and calculations (simple) and two tasks that required high number of variables/information cues and calculations (complex). For both simple tasks existing CFT IS literature (Speier, 2006) tasks from Production Operations Management domain and was adapted to a more generic Financial Accounting Domain. Unlike study #1, in study #2 each subject performed all tasks in both representation formats. In order to avoid potential bias of using the same answer from the same task and different representation influencing answer in another representation, a slightly modified version of tasks was created while preserving tasks' level of complexity and task type.

In simple-spatial task, the original version of task, like in study #1, asked subjects asked to identify a month in which Actual Unit Rate is the highest for all three factories, while in slightly modified version subjects were asked to identify a month in which Actual Net Income is the highest for all three work centers. While both had a single optimal answer, they differed in which month (answer) was the correct one to eliminate the potential bias. Although slightly different, using Wood's (1986) methodology for assessment, the two tasks were identical in terms of complexity while still being spatial in nature. These two tasks were used for Cell 1 (Tabular Representation) and Cell 2 (Graphical Representation) (See Appendix - Figure 16 and Figure 17).

In simple-symbolic task, the original version of task in study #1 was used. It asked subjects to obtain specific data by directly extracting information regarding unit rates for a specific location and a specific month. Once unit rates are located, they are subtracted from each other resulting in correct answer. A slightly modified task was added to avoid a potential bias while allowing to test with alternate representation. As in other tasks, using Wood's (1986) methodology for assessment, the two tasks were identical in terms of complexity while still being symbolic in nature. These two tasks were used for Cell 3 (Tabular Representation) and Cell 4 (Graphical Representation) (See Appendix – Figure 18 and Figure 19 for both tasks).

In complex-spatial task, the original version of task in study #1 was kept (subjects were asked to use existing information for 6 firms to assess which companies meet both financial scenarios where each scenario has 3 and/or conditions) while slightly modified task (identical in terms of complexity while still being spatial in nature) was added to avoid a potential bias. These two tasks were used for Cell 5 (Tabular Representation) and Cell 6 (Graphical Representation) (See Appendix – Figure 20 and Figure 21 for both tasks).

Lastly, in complex-symbolic task, the original version of task in study #1 was also used (In the firm investment task, subjects were provided with five different balance sheet (liabilities) line items/categories associated with six firms. Subjects were asked to determine which firms to invest based on scenario conditions) and slightly modified task (identical in terms of complexity and nature) was added to avoid a potential bias. These two tasks were used for Cell 7 (Tabular Representation) and Cell 8 (Graphical Representation) (See Appendix – Figure 22 and Figure 23 for both tasks).

4.2.2.2 Representation

Same as is Study #1. See 4.1.2.2

4.2.3 Subjects

As in study # 1, subjects were recruited from various business classes with both undergraduate and graduate students at Cleveland State University. In addition to students receiving partial course credit (as in study #1), $10 gift certificate was awarded for participation in study #2. Participants were still eligible to receive one of three $50 rewards for performance in terms of accuracy per unit of time. All participants performed all 8 experimental tasks in random order.

4.2.4 Experiment Procedure and Set-up

Data collection for Study #2 occurred in two steps. In the first step, volunteer subjects were provided with an online survey (Qualtrics online tool) to collect subject's background information such as age, gender, class standing, major and years of work experience to describe the sample population of the study. The same survey was used to collect 18 items describing subjects' Need for Cognition. The order of NFC questions was randomized and the original wording was maintained where 9 out of 18 are reverse-worded. In the last portion of the survey subjects were asked to solve 4 problems measuring their level of accounting knowledge. At the end of the survey students were asked to their student id and name in order to allow for linkage with the eye-tracking portion of data collection. There was no time limit placed on the survey.

Once subjects completed the online survey, each participant scheduled one-on-one experimental session to perform 8 experimental tasks and collect eye-tracking and self-reported (perceptual) measures of cognitive effort along with task performance measures of time and accuracy. In total, 35 one-hour sessions were conducted in 20 day period. Standard process and script was followed for each participant. The script consisted of brief investigator introduction and the explanation of the study. It was followed by explanation of procedures, risk/benefits, discomforts, compensation, and data confidentiality. Once subject was fully informed, consent form was signed and experiment initiated (See Informed Consent – Study #2 in Appendix).

Experimental sessions took place in a small lab consisting of computer (laptop), monitor and eye-tracking equipment.

Figure 10: Gazepoint Eye-Tracking Lab (BU440)

All subjects used the same equipment - a 21'' monitor connected to a brand new HP EliteBook 8570p with Windows 7 Operating System and Intel's Core i5 processor and 4GB RAM. GP3 Eye Tracker by Gazepoint was connected to HP computer and placed securely underneath the monitor. GP3 Eye Tracker manufacturer reported specification include accuracy of 0.5 – 1 degree of visual angle, 60Hz update rate, 5 point or 9 point calibration and allows for 25cm x 11cm (horizontal x vertical) movement and ±15 cm range of depth movement. GP3 specifications meet the required eye fixation speed and accuracy measures required for this study and those specifications (or lower) have been used in academic research in the past. HP computer used met GP3 Eye-tracker manufacturer's system requirements: Intel Core i5 or faster, 4 GB RAM, and Windows 7/8/XP/Vista, Lynx or Mac OS.

Gazepoint eye-tracking software was installed to enable data capture: 1) Gazepoint Control software was used in the process of calibration, and 2)

Gazepoint Analysis 2.2.0 software was used in data collection, data extraction, experiment monitoring and analysis. Combined GP3 Eye-Tracker, Gazepoint Control and Gazepoint Analysis are bundled and labeled by the manufacturer as Gazepoint Analysis Professional product and represent “all-in-one eye tracking software for UX usability study and academic research”[2].

Following the script and after obtaining the signed informed consent form, each subject was asked to sit in front of the monitor and went through an approximately 10 second process of 9-point calibration. The process of calibration ensured that eye-tracking equipment was accurately capturing subjects’ eye movement. Once calibration process was successfully completed, randomly selected eye-tracking software’s project folder representing one of the 8 experimental cells was initiated by investigator. This triggered automatic monitor display of a problem/task and table(s) or graph(s) containing information needed to provide answer(s) to the problem while recording subject’s eye-movement, namely fixation count and duration. Task was completed by subjects verbalizing the multiple choice letter(s) corresponding to the answers he/she deemed accurate. At that moment investigator stopped the recording of the eye movement and noted time and subject’s answer(s). After completion of the task the user was asked to indicate via online survey agreement with statements relative to their self-reported perception of the task. These statements represented self-reported scales of Cognitive Effort. During task performance, the investigator was located behind subject and was able to monitor on his own

[2] http://gazept.com/portfolio-items/analysis-pro/

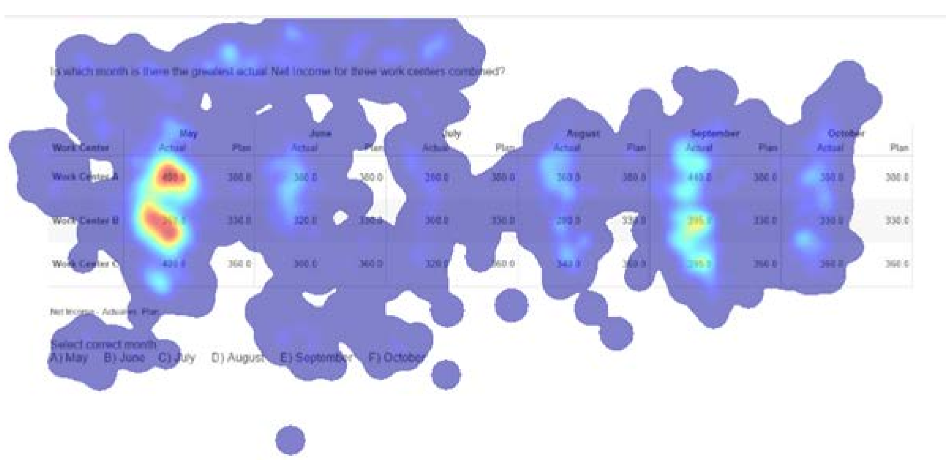
screen in real time both the quality of eye pupil capture by the eye tracker along with the fixation and gaze movement on the screen. Investigator also noted if any of the recordings need to be reviewed for potential recording issues.

This process was repeated 8 times for each subject so that each subject performed all tasks aligned with 8 experimental cells once. After each task the subject was asked if there was a need for a short break and no subject indicated the need to stop due to fatigue or any other reason. The order of tasks for each subject was randomized in advance using randomization algorithm. After all 8 tasks were completed, participant would enter his/her student id and name along with investigator supplier experiment id (from 0 – 34). This enabled for the linkage between first online survey data collection and data collected during one-on-one experimental session and at the same time allowed to better preserve confidentiality and potential anonymity of data after study's completion.

The experiment ended with 5-10 minute debriefing. During debrief the recording of the last task was replayed as it was the easiest to recall. During replay subjects were ask to verbalize what they were doing and to explicitly state if they believe eye fixations (movement, duration and frequency) accurately reflect their actions. All subjects unequivocally stated that captured recording represent their viewing pattern (fixations locations and movement) and its intensity (fixation duration). In addition to replaying last task's recording (for example: Simple Spatial Graphical), time permitting, the same type of task but with different representation format (for example Simple Spatial Tabular) was also replayed so that the subject may further verbalize the impact of different representation formats on the same task. As the last step, participant signed the form verifying recorded time and answers for each task and acknowledging the receipt of $10 gift certificate. Although there was no explicit time limit to this study, all one-on-one experimental sessions were completed in no less than 45 minutes and not longer than 55 minutes.

After all one-on-one sessions were completed, I replayed and watched all 280 (35*8) recordings (some more than once) in order to, independently of notes taken during experiment, assess the usability of each recording. Recordings for user id 14 and 22 were deemed unusable. I then proceeded to review experimental notes and verified that in those notes a comment was made regarding a potential usability of recordings associated with user id 14 and 22. Common issue of occasional inability for eye-tracker to correctly identify pupil due to light reflection of subject's eye-glasses was the reason for unusable recordings (Holmqvist et al., 2011).

Figure 11: Sample Single User Fixation Heat Map



For illustration purposed, figure 11 provides an actual image of a single user eye gaze/fixation behavior during study #2 experiment. Figure 12 provides the same for all 32 participants in combined.

Figure 12: Aggregate Heatmap

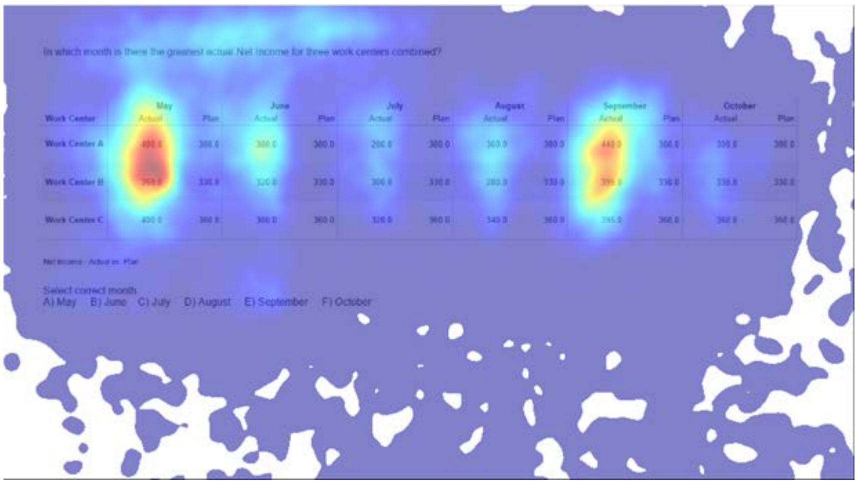
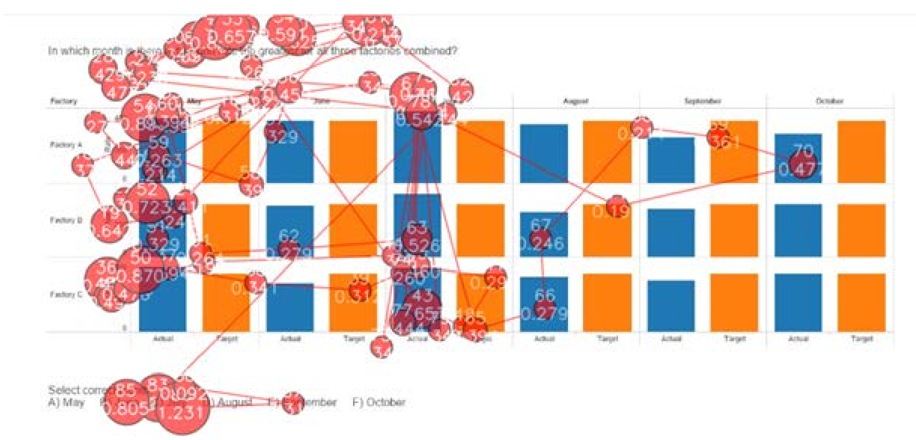


Figure 13 provides the image of single user fixations, their order and duration during task performance.

Figure 13: Sample SIngle User Fixation Map



Data was then exported from Gazepoint Analysis software for each cell/project and each user. The export generated 280 files (35*8). Additionally, data was exported from both Qualtrics online surveys (first data collection that includes background demographic information, items for NFC, and data for measuring financial accounting domain knowledge + self-reported cognitive effort data during one-on-one experiments). A series of queries was used to link and prepare data for import into SPSS statistical analysis tool for hypotheses testing and further analysis.

CHAPTER V

5. RESULTS AND DATA ANALYSIS

Following collected data export and appropriate data combining, data was exported and loaded into SPSS for analysis. In this section I will present the results and analysis for both studies in sequence.

5.1 Study #1 - Results

74 subjects volunteered to participate in Study #1. Data for 6 was unusable and subsequent analysis was conducted using data from 68 subjects (43 % male and 57% female) who each participated in 4 out of 8 experimental cells so that in that each cell had N=34. The median age of the participants was 21 and the average age was 23.5 (SD=7.22) with all but 1 participant being undergraduate students. Task relevant work experience data was collected as well and 25% of participants had at least some work experience in professional or technical job, while 17.6% had some work experience as a manager or proprietor. The average number of years in professional or technical role was 0.83 (SD=2.064) and 0.35 (SD=0.91) as a manger or proprietor. Participants came from wide number of business majors. Table 20 provides participant summary.

Gender		Student Type		Major		Age		Exp. (Yrs)	Role Prof./ Mgr.
Male:	29	Undergrad	67	Accounting	14	18 - 29	61	0	51/56
Female:	39	Grad	1	CIS	4	30 - 39	3	1 - 5	14/12
				MGT & OSCM	12	40 +	4	5 - 10	2/0
				MKT	17			10 +	1/0
				G. Business & Other	21				

Table 20: Sample Description - Study #1

Self-reported cognitive effort 6-item scale Cronbach's alpha was .779 and it exceeded 0.7 acceptable threshold (Nunnally, 1978), therefore the average score of all 6-items was used to measure self-reported perception of cognitive effort. Similarly, NFC 18-item scale Cronbach alpha of 0.835 exceeded 0.7 threshold and average score based on all 18 items was used to test its impact in H5 and H6.

Manipulation check for Task Complexity was completed by asking subjects their perceptions of complexity on scale 1 through 7. The difference in mean values for complex (M=5.75, SD=2.53) and simple (M=3.49, SD=2.25) was found to be significant (F(68)= 95.675, p<0.01) and in expected direction.

5.1.1 Study #1 Results – H1 through H4

A 2 (Task Complexity – Simple vs Complex) by 2 (Task Type – Spatial vs. Symbolic) by 2 (Format – Graph vs Table) between-subject ANOVA (Table 21) revealed a significant main effect of Task Complexity, $F(1,264)=31.911$; $p<0.001$; $MSE=24.320$; $\eta_p^2=0.108$. No significant effect was revealed, however, for Task Type, $F(1,264) = 2.478$; $p=0.117$; $MSE=1.889$; $\eta_p^2=0.009$ and Format, $F(1,264) = 1.038$; $p=0.309$; $MSE=0.791$; $\eta_p^2=0.004$.

To test Hypotheses 1 through 4, we need to look for statistically significant effect of interaction between Task Type and Task Representation on CE_{SR}. The analysis of variance showed a significant interaction effect of Task Type * Representation $F(1,264)= 5.557$; $p=0.019$; $MSE=4.250$; $\eta_p^2=0.021$. No other interaction combination between Task Complexity, Task Type, and Format was found to be significant.

Source	df	Mean Square	F	Sig.	P. Eta Squared	Obs. Power
Task Complexity	1	24.320	31.911	.000	.108	1.000
Task Type	1	1.889	2.478	.117	.009	.348
Format	1	.791	1.038	.309	.004	.174
Task Complexity * Task Type	1	2.118	2.779	.097	.010	.383
Task Complexity * Format	1	.721	.946	.332	.004	.163
Task Type * Format	1	4.250	5.577	.019	.021	.653
Task Complexity * Task Type * Format	1	1.021	1.340	.248	.005	.211
Subject	1					
Error	264					
Total	272					
Model R Squared = 14.9 (Adjusted R Squared = 12.6)						

Table 21: Results of ANOVA - Study #1

Since significant effect of interaction was detected, pairwise t-test was conducted to evaluate if difference in means between cells specifically hypothesized in H1 through H4 are significant. Table 22 provides a summary of means and standard error for each experimental cell. Pairwise comparison of direction and statistical significance of mean difference for Cells 2 – 1, 3 – 4, 6 – 5, and 7 – 8 (See Table 23) was conducted to evaluate H1 through H4 using Bonferroni adjustment for multiple comparison[3]. Because H1 – H4 are theory-supported directional hypotheses one tail significance is adopted in interpretation of the results.

Task Complexity	Task Type	Format	Cell	Mean	Std. Error	N
Simple	Spatial	Graph	1	4.637	.150	34
		Table	2	4.554	.150	34
	Symbolic	Graph	3	4.775	.150	34
		Table	4	4.436	.150	34
Complex	Spatial	Graph	5	5.186	.150	34
		Table	6	5.554	.150	34
	Symbolic	Graph	7	5.216	.150	34
		Table	8	4.838	.150	34

Table 22: Descriptive Statistics - Study #1

Pairwise comparison of CE_{SR1} mean difference (Table 23) between Simple-Spatial task – Graph (Cell 2; M=4.554; SD=0.150) and Simple-Spatial task – Table (Cell 1; M=4.637; SD=0.150) of .083 (SD=0.212) was not significant (p=1.0) therefore *H1 was not supported*. Pairwise comparison of CE_{SR1} mean difference between Simple-Symbolic task – Table (Cell 3; M=4.775; SD=0.150)

[3] Hypotheses H1 though H4 specifically test/evaluate difference between apriori specified pairs of cells. Literature makes suggestion that therefore no adjustment for multiple comparisons needs to be made. For the purpose of this dissertation, I used Bonferroni method as it is a standard in IS literature and in this context a more conservative method. However, analysis was rerun without adjustment (Fisher's LSD) and when using that procedure H3 and H4 were supported and those results were made available in results table (Table 23).

and Simple-Symbolic task – Graph (Cell 4; M=4.436; SD=0.150) of -.338 (SD=0.212) was not significant (p=1.0), therefore *H2 was not supported*. Pairwise comparison of CE_{SR1} mean difference between Complex-Spatial task – Graph (Cell 6; M=5.554; SD=0.150) and Complex-Spatial task – Table (Cell 5; M=5.186; SD=0.150) of -0.368 was not significant (p=1.0), therefore *H3 was not supported*. Lastly, pairwise comparison of CE_{SR1} mean difference between Complex-Symbolic task – Table (Cell 7, M=5.216; SD=0.150) and Complex-Symbolic task – Graph (Cell 8; M=4.838; SD=0.150) of -.377 was not significant (p=1.0), therefore *H4 was not supported*.

Dependent Variable: CE_{SR1}

(I) Cell_id	(J) Cell_id	Mean Difference (I-J)	Std. Error	Sig.[a]	90% Confidence Interval for Difference[a] Lower Bound	Upper Bound
2	1	.083	.212	1.000	-.539	.706
3	4	-.338	.212	1.000	-.961	.284
6	5	-.368	.212	1.000	-.990	.255
7	8	-.377	.212	1.000	-1.000	.245

Based on estimated marginal means

a. Adjustment for multiple comparisons: Bonferroni.

*. The mean difference is significant at the .10 level.

Table 23: Pairwise Comparisons - Study #1

Table 24 provides the summary of findings on the hypothesized impact of Task type and Representation fit on subjects' cognitive effort.

Hypotheses 1 - 4	**Cells**	**Cell Mean Diff in CE_{SR1}**	**Findings** Bonferroni	LSD
H1: For **Simple-spatial** tasks, spatial (**graph**) information presentation formats	2 vs 1	.083	Not Supported	Not Supported

result in **lower** cognitive effort than symbolic (**table**) formats.				
H2: For **Simple-symbolic** tasks, symbolic (**table**) information presentation formats results in **lower** cognitive effort than spatial (**graph**) formats	3 vs 4	-.338	Not Supported	Not Supported
H3: For **Complex-spatial** tasks, spatial (**graph**) information presentation formats result in **lower** cognitive effort than symbolic (**table**) formats	6 vs 5	-.368	Not Supported	Supported*
H4: For **Complex-symbolic** tasks, symbolic (**table**) information presentation formats result in **lower** cognitive effort than spatial (**graph**) formats.	7 vs 8	-.377	Not Supported	Supported*

*Sig <0.10 **Sig<0.05

Table 24: H1-H4 Summary - Study #1

5.1.2 Study #1 Results – H5 and H6

Before proceeding with testing hypotheses H5 and H6 correlations of variables involved are summarized in Table 25.

Correlations

		CE_{SR1}	Accuracy	Time	Need for Cognition
CE_{SR1}	Pearson Correlation	1	-.168**	.371**	.180**
	Sig. (2-tailed)		.005	.000	.003
	N	272	272	272	272
Accuracy	Pearson Correlation	-.168**	1	-.227**	.099
	Sig. (2-tailed)	.005		.000	.103
	N	272	272	272	272
Time	Pearson Correlation	.371**	-.227**	1	.045
	Sig. (2-tailed)	.000	.000		.460
	N	272	272	272	272
Need for Cognition	Pearson Correlation	.180**	.099	.045	1
	Sig. (2-tailed)	.003	.103	.460	
	N	272	272	272	272

Correlations

		CE_{SR1}	Accuracy	Time	Need for Cognition
CE_{SR1}	Pearson Correlation	1	-.168**	.371**	.180**
	Sig. (2-tailed)		.005	.000	.003
	N	272	272	272	272
Accuracy	Pearson Correlation	-.168**	1	-.227**	.099
	Sig. (2-tailed)	.005		.000	.103
	N	272	272	272	272
Time	Pearson Correlation	.371**	-.227**	1	.045
	Sig. (2-tailed)	.000	.000		.460
	N	272	272	272	272
Need for Cognition	Pearson Correlation	.180**	.099	.045	1
	Sig. (2-tailed)	.003	.103	.460	
	N	272	272	272	272

**. Correlation is significant at the 0.01 level (2-tailed).

Table 25: Correlations - Study #1

CE_{SR1} was negatively correlated with Accuracy ($r=-0.168$, $p<0.01$) and positively correlated with Time ($r=0.371$, $p<0.01$) and Need for Cognition ($r=0.180$, $p<0.01$). Time was negatively correlated with Accuracy ($r=-0.227$, $p<0.01$).

Multiple regression tests were conducted to test H5 and H6 where expectation was for the relationship between cognitive effort and time (H5) and accuracy (H6) to be moderated by the level of participants Need for Cognition. Using mean centered CE_{SR1} and NFC score (for interaction term), regression test found statistically significant direct impact of CE_{SR1} on Time but no direct effect NFC nor the interaction between the two was detected (Adjusted R

Square=13.2%, $F(272)=14.708$, $p=0.000$). Therefore hypothesized positive impact of CE_{SR1} * NFC on Time (H5) was not supported. Regression test of the impact of CE_{SR1} and NFC on Accuracy found statistically significant direct impact of both CE_{SR1} and NFC but no effect of interaction between the two on Accuracy was detected. The overall model was significant ($F(272)=3.23$, $p<0.05$) with Adjusted R Square=2.4%, however hypothesized impact of CE_{SR1} * NFC on Accuracy (H6) was not supported (Table 26).

	Time	Accuracy
Constant	108.818 (4.394)	.890 (.029)
Cognitive Effort (CE_{SR})	29.910*** (4.797)	-.028** (.011)
Need for Cognition (NCF)	-2.196 (5.602)	.028** (.013)
CE_{SR} x NFC	-5.771 (5.909)	.007 (.014)
R Square	0.141	0.035
Adjusted R Square	0.132	0.024
No of Observations	272	

Standard Error are noted in parenthesis
,* indicates significance at the 95% and 99% level, respectively

Table 26: H5-H6 Regression - Study #1

Regression models for both Time and Accuracy were tested with Domain Knowledge as well (as first variable in regression). Table 27 summarizes results for H5 and H6[4].

[4] The impact of Domain Knowledge was not significant

Hypotheses 5 - 6	Findings
H5: Increase in Cognitive effort increases the amount of time required for a decision and this relationship is amplified with increase in individual's Need for Cognition	Not Supported
H6: Increase in Cognitive effort decreases decision accuracy and this relationship is amplified with decrease in individual's Need for Cognition	Not Supported

Table 27: H5-H6 Summary - Study #1

Given lack of support for suggested hypotheses, mediation test for cognitive effort * NFC interaction was not conducted.

5.2 Study #2 - Results

As discussed previously, 35 subjects volunteered to participate in Study #2. Data for 2 subjects was eliminated due to the poor quality of eye-tracking measure collected during this study. One subject was eliminated as perceptual measures of Cognitive Effort were not collected. Therefore, subsequent analysis was conducted using data from 32 subjects (37.5% male and 62.5% female). The median age of the participants was 28 and the average age was 30 (SD=8.75). 77% of participants were undergraduate students. Task relevant work experience data was collected as well and 40% of participants had at least some work experience in professional or technical job, while almost 18% had some work experience as a manager or proprietor. The average number of years in professional or technical role was 3.66 (SD=6.01) and 2.00 (SD=4.39) as a manger or proprietor. Participants came from wide number of business majors. Table 28 provides participant summary.

Gender		Student Type		Major		Age		Yrs	Prof./ Mgr.
Male:	12	Undergrad	23	CIS & IST	4	19 - 29	17	0	19/23
Female:	20	Grad	9	FIN	6	30 - 39	13	1 - 5	5/4
				MGT & OSCM	4	40 +	2	5 - 10	3/3
				MKT	11			10 +	5/2
				Other	5				

Table 28: Sample Description - Study #2

Self-reported cognitive effort 6-item scale Cronbach's alpha of 0.78 exceeded 0.7 acceptable threshold (Nunnally, 1978) and the average score of all 6-items was used to measure self-reported perception of cognitive effort. Similarly, NFC 18-item scale Cronbach's alpha of 0.811 exceeded 0.7 threshold and average score based on all 18 items was used to test its impact in H5 and H6.

Manipulation check for Task Complexity was completed by asking 32 subjects their perceptions of task complexity on scale 1 through 7. The difference in mean values for complex ($M=5.72$, $SD=1.427$) and simple ($M=2.89$, $SD=1.234$) was found to be significant ($F(32)=132.678$, $p<0.01$) and in expected direction.

Manipulation check for Task Type was completed by asking subjects[5] their perception of the level of needs for data relationships and the need for precise values on scale 1 through 10. The combined score for question 1 and reverse coded score for question 2 was used to assess the subjects' ability to detect the difference in Task Type. The difference in mean values for spatial ($M=10.19$, $SD=1.554$) and symbolic ($M=9.5$, $SD=1.293$) was found to be significant ($F(31)=7.456$, $p<0.01$) and in expected direction. In addition to these

[5] One participant did not answer manipulation question(s)

manipulation checks it needs to be noted that designed tasks followed accepted methodology on task complexity (Wood, 1986) along with adopting 6 out 8 tasks from Speier (2006).

Bivariate correlation 0f variables (Table 29) used in study's hypotheses showed that Fixation Duration (CE_{FD}) is positively correlated with Time (r=0.159, p=0.01), Fixation Count (CE_{FC}) is positively correlated with Time (r=0.972, p=0.000) and self-reported Cognitive Effort (CE_{SR2}) (r=0.420, p=0.000) and negatively correlated with Accuracy (r=-0.233, p=0.000). Time is negatively correlated with Accuracy (r=-0.232, p=0.000) and CE_{SR} (r=-0.422, p=0.000). Lastly, Accuracy is negatively correlated with CE_{SR} (r=-0.159, p=0.000). All significant correlations are in expected direction, however correlation of CE_{FC} with Time of (r=0.972, p=0.000) is extremely high and indicates that they may potentially measure the same construct.

Correlations

		CE_{FD}	CE_{FC}	Time	Accuracy	CE_{SR2}	NFC
CE_{FD}	Pearson Correlation	1	.071	**.159***	.027	.084	-.047
	Sig. (2-tailed)		.261	.011	.673	.180	.450
	N	256	256	256	256	256	256
CE_{FC}	Pearson Correlation	.071	1	**.972****	**-.233****	**.420****	-.024
	Sig. (2-tailed)	.261		.000	.000	.000	.702
	N	256	256	256	256	256	256
Time	Pearson Correlation	.159*	**.972****	1	**-.232****	**.422****	-.023
	Sig. (2-tailed)	.011	.000		.000	.000	.718
	N	256	256	256	256	256	256
Accuracy	Pearson Correlation	.027	**-.233****	**-.232****	1	**-.159***	.006

	Sig. (2-tailed)	.673	.000	.000		.011	.920
	N	256	256	256	256	256	256
CE_{SR2}	Pearson Correlation	.084	**.420****	**.422****	**-.159***	1	-.014
	Sig. (2-tailed)	.180	.000	.000	.011		.824
	N	256	256	256	256	256	256
NFC	Pearson Correlation	-.047	-.024	-.023	.006	-.014	1
	Sig. (2-tailed)	.450	.702	.718	.920	.824	
	N	256	256	256	256	256	256

*. Correlation is significant at the 0.05 level (2-tailed).

**. Correlation is significant at the 0.01 level (2-tailed).

Table 29: Correlations - Study #2

Participant's tested domain knowledge was not correlated with two remaining measures of cognitive effort and was not found to be a significant factor for CE_{FD} and CE_{SR} and was therefore excluded from the analysis of treatments on cognitive effort.

5.2.1 Study #2 - Results – H1 through H4

5.2.1.1 Cognitive Effort measured through Fixation Duration (CE_{FD})

Repeated measures Analysis of Variance (Table 30) showed a main effect of Task Complexity ($F(1,31)=8.352$, $p=0.007$, $\eta_p^2=212$) and Task Type ($F(1,31)=4.282$, $p=0.047$, $\eta_p^2=0.121$). The Analysis of Variance also showed interaction effect of Task Complexity * Task Type ($F(1,31)=51.939$, $p=0.000$, $\eta_p^2=0.626$), Task Complexity * Representation ($F(1,31)=7.522$, $p=0.01$, $\eta_p^2=0.195$), Task Type * Representation ($F(1,31)= 10.58$, $p=0.003$, $\eta_p^2=254$), and

3 way interaction Task Complexity * Task Type * Representation ($F(1,31)=15.889$, $p=0.000$, $\eta_p^2=0.339$). Representation was the only variable not exhibiting statistically significant main effect on CE_{FD} ($F(1,31)=0.651$, $p=0.426$, $\eta_p^2=0.021$)

To test Hypotheses 1 through 4, we need to look for statistically significant effect of interaction between Task Type (spatial vs symbolic) and Representation (table vs graph) on CE_{FD}. The repeated measures ANOVA detected statistically significant effect of both Task Type * Representation and 3 way interaction Task Complexity * Task Type * Representation.

Source	df	Mean Square	F	Sig.	Partial Eta Squared	Observed Power
Task_Complexity	1	.007	8.352	.007	.212	.799
Task_Type	1	.002	4.284	.047	.121	.518
Representation	1	.001	.651	.426	.021	.122
Task_Complexity * Task_Type	1	.042	51.939	.000	.626	1.000
Task_Complexity * Representation	1	.005	7.522	.010	.195	.757
Task_Type * Representation	1	.012	10.580	.003	.254	.883
Subjects	31					
Error	217					
Total	255					

Table 30: ANOVA (CE_{FD}) Results - Study #2

Since desired effect of interaction was detected, pairwise t-test of each interaction (experimental cell) was conducted to evaluate if difference in means between cells specifically hypothesized in H1 through H4 are significant. Because H1 – H4 are theory-supported directional hypotheses one tail significance was adopted in interpretation of the results. Bonferroni method is used to adjust for multiple comparisons (8 cells) as is de-facto standard in IS literature, however, it should be noted that hypotheses H1 though H4 specifically test/evaluate difference between apriori specified pairs of cells and therefore an argument could be made that no adjustment for multiples comparisons needs to be made[6].

Task Complexity	Task Type	Format	Cell	Mean	Std.	N
Simple	Spatial	Graph	1	.37765	.03669	32
		Table	2	.35863	.04376	32
	Symbolic	Graph	3	.38446	.04973	32
		Table	4	.41528	.05385	32
Complex	Spatial	Graph	5	.39070	.03684	32
		Table	6	.37588	.03155	32
	Symbolic	Graph	7	.36835	.04129	32
		Table	8	.35937	.04355	32

Table 31: Descriptive Statistics - Study #2 - CE_{FD}

Pairwise comparison of direction and statistical significance of mean difference for Cells 2 – 1, 3 – 4, 6 – 5, and 7 – 8 (See Table 31 for descriptive statistics and Table 32 for mean differences) was conducted to evaluate H1 through H4. Pairwise comparison of CE_{FD} mean difference between Simple-Spatial task – Graph (Cell 2; M=0.359; SD=0.037) and Simple-Spatial task – Table (Cell 1; M=0.35863; SD=0.044) of -0.019 (SD=0.006) was significant (p=0.069) and in expected direction therefore *H1 was supported*. Pairwise comparison of CE_{FD} mean difference between Simple-Symbolic task – Table (Cell 3; M=0.384; SD=0.050) and Simple-Symbolic task – Graph (Cell 4; M=0.415; SD=0.053) of -0.031 (SD=0.009) was significant (p=0.048) and in expected direction, therefore *H2 was supported*. Pairwise comparison of CE_{FD} mean difference between Complex-Spatial task – Graph (Cell 6; M=0.376; SD=0.031)

[6] Pairwise comparison was rerun using LSD method and similar results were found as when using Boneferroni.

and Complex-Spatial task – Table (Cell 5; M=0.391; SD=0.032) of -0.019 (SD=0.003) was significant (p=0.002) and in expected direction therefore *H3 was supported*. Lastly, pairwise comparison of CE_{FD} mean difference between Complex-Symbolic task – Table (Cell 7; M=0.368; SD=0.041) and Complex-Symbolic task – Graph (Cell 8; M=0.359; SD=0.044) of 0.009 (SD=0.009) was not significant (p=1.000), therefore *H4 was not supported*.

(I) Cells	(J) Cells	Mean Difference (I-J)	Std. Error	Sig.[a]	90% Confidence Interval for Difference[a] Lower Bound	Upper Bound
2	1	-.019*	.006	.069	-.037	-.001
3	4	-.031*	.009	.048	-.059	-.002
6	5	-.015*	.003	.002	-.025	-.005
7	8	.009	.009	1.000	-.019	.037

Based on estimated marginal means

*. The mean difference is significant at the .10 level/a. Adjustment for multiple comparisons: Bonferroni.

Table 32: Pairwise Comparisons - CE_{FD} – Study #2

Table 33 summarizes the findings on the hypothesized impact of Task Type and Representation fit on subjects' CE_{FD}.

Hypotheses 1 - 4	Cells	Cell Mean Diff in CE_{FD}	Findings[7]
H1: For **Simple-spatial** tasks, spatial (**graph**) information presentation formats result in **lower** cognitive effort than symbolic (**table**) formats.	2 vs 1	-.019*	Supported
H2: For **Simple-symbolic** tasks, symbolic (**table**) information presentation formats results in **lower** cognitive effort than spatial (**graph**) formats	3 vs 4	-.031**	Supported
H3: For **Complex-spatial** tasks, spatial (**graph**) information presentation formats result in **lower** cognitive effort than symbolic (**table**) formats	6 vs 5	-.015**	Supported

[7] The same support significance using Bonferroni or LSD

H4: For **Complex-symbolic** tasks, symbolic (**table**) information presentation formats result in **lower** cognitive effort than spatial (**graph**) formats.	7 vs 8	.009	Not Supported

*Sig <0.10 **Sig<0.05

Table 33: H1-H4 Summary (CE_{FD}) - Study #2

5.2.1.2 Cognitive Effort measured through Fixation Count (CE_{FC})

Although CE_{FC} appeared to be measuring the same phenomenon as Time and will not be used to assess its impact Time and Accuracy, the analysis of the impact of theorized fit on CE_{FC} was conducted to enhance our understanding of eye-tracking based measures of Cognitive effort.

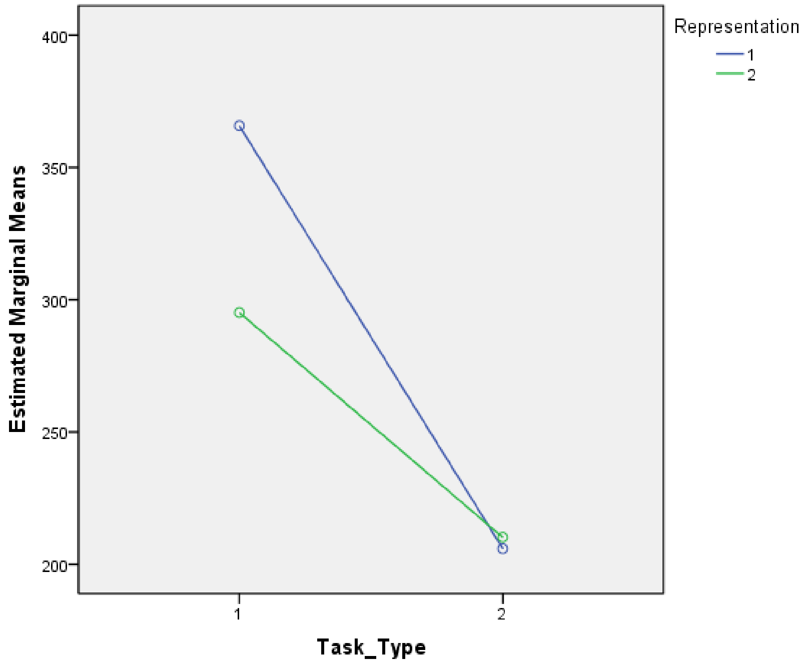
The Analysis of Variance (Table 34) showed significant impact of the main effect of Task Complexity ($F(1,31)= 252.204$; $p=0.001$; $\eta_p^2=0.891$), Task Type ($F(1,31)= 140.026$; $p=0.001$; $\eta_p^2=0.819$), Representation ($F(1,32)= 13.965$; $p=0.001$; $\eta_p^2=0.311$), as well as interaction effects of Task Complexity * Task Type ($F(1,32)= 72.847$; $p=0.001$; $\eta_p^2=0.701$), Task Complexity * Representation ($F(1,31)= 5.962$; $p=0.021$; $\eta_p^2=0.161$), and Task Type * Representation ($F(1,32)= 11.330$; $p=0.002$, $\eta_p^2=0.268$)

Source	df	Mean Square	F	Sig.	P. Eta Squared	Obs. Power[a]
Task Complexity	1	4986568	252.204	.000	.891	1.000
Task Type	1	958563	140.026	.000	.819	1.000
Representation	1	70390	13.965	.001	.311	.951
Task Complexity * Task Type	1	670863	72.847	.000	.701	1.000
Task Complexity * Representation	1	47008	5.962	.021	.161	.657
Task Type * Representation	1	89738	11.330	.002	.268	.903
Task Complexity*Task Type* Representation	1	706	.088	.768	.003	.060
Subjects	31					
Error	217					
Total	255					

Table 34: ANOVA (CE_{FC}) Results

Although the impact of three way interaction between all three factors: Task Complexity (simple vs complex), Task Type (spatial vs symbolic) and Representation (table vs graph) on CE_{FC} is not significant, because CFT and CFT-supported Hypotheses 1 through 4 suggest interaction between Task Type and Representation, the interaction between those two treatments warrants closer understanding. Figure 14 shows how significant interactions between Task Type (1=Spatial, 2=Symbolic) and Representation (1=Table, 2=Graph), influences larger difference for spatial tasks while for symbolic tasks CE_{FC} is minimal.

Figure 14: Task Type * Representation (CE_{FC}) Interaction



In order to understand whether the mean difference in CE_{FC} between table and graph was significant for only simple, only complex or for both simple and complex tasks, a pairwise comparison of mean differences between experimental cells aligned with H1 – H4 was completed.

Task Complexity	Task Type	Format	Cell	Mean	Std.	N
Simple	Spatial	Graph	1	159.72	67.012	32
		Table	2	119.53	52.892	32
	Symbolic	Graph	3	105.59	62.731	32
		Table	4	133.66	67.483	32
Complex	Spatial	Graph	5	571.66	228.146	32
		Table	6	470.63	161.619	32
	Symbolic	Graph	7	306.13	149.386	32
		Table	8	286.63	86.269	32

Table 35: Descriptive Statistics - Study #2 - CE_{FC}

Pairwise comparison of mean difference (See Table 35 for descriptive statistics and Table 36 for mean differences) between Simple-Spatial task – Graph (Cell 2; M=119.53; SD=52.89) and Simple-Spatial task – Table (Cell 1; M=159.72; SD=67.01) of -40.188 (SD=10.36) was significant (p=0.014) and in expected direction therefore *H1 was supported*. Comparison of mean differences for complex version of spatial tasks (Complex-Spatial task – Graph (Cell 6; M=470.63; SD=161.62) and Complex-Spatial task – Table (Cell 5; M=571.66; SD=228.15)) of -101.031 (SD=30.28) was significant (p=0.062) and in expected direction therefore *H3 was supported*. To ensure that lack of statistical significance for Symbolic task is not due to Simple and Complex versions' impact on CE_{FC} cancelling each other, a pairwise comparison of CE_{FC} mean difference between Simple-Symbolic task – Table (Cell 3; M=105.59; SD=62.73) and Simple-Symbolic task – Graph (Cell 4; M=133.66; SD=67.48) and CE_{FC} mean difference between Complex-Symbolic task – Table (Cell 7; M=306.13; SD=141.39) and Complex-Symbolic task – Graph (Cell 8; M=286.63; SD=86.27) was evaluated. Both lacked significance (p=0.506 and p=1.000) therefore *H2 and H4 were not supported*[8].

(I) Cells	(J) Cells	Mean Difference (I-J)	Std. Error	Sig.[a]	90% Confidence Interval for Difference[a] Lower Bound	Upper Bound
2	1	-40.188*	10.364	.014	-72.870	-7.505
3	4	-28.063	11.240	.506	-63.506	7.381
6	5	-101.031*	30.282	.062	-196.521	-5.541
7	8	19.500	25.530	1.000	-61.004	100.004

Based on estimated marginal means

[8] H2 was supported when using LSD in addition to H1 , H2 and H3 being Sig<0.001

(I) Cells	(J) Cells	Mean Difference (I-J)	Std. Error	Sig.[a]	90% Confidence Interval for Difference[a] Lower Bound	Upper Bound
2	1	-40.188*	10.364	.014	-72.870	-7.505
3	4	-28.063	11.240	.506	-63.506	7.381
6	5	-101.031*	30.282	.062	-196.521	-5.541
7	8	19.500	25.530	1.000	-61.004	100.004

Based on estimated marginal means

*. The mean difference is significant at the .10 level.

a. Adjustment for multiple comparisons: Bonferroni.

Table 36: Pairwise Comparisons (CE_{FC}) - Study #2

Table 37 provides the summary of findings on the hypothesized impact of Task Type and Representation fit on cognitive effort measured through CE_{FC}.

Hypotheses 1 - 4	**Cell Mean Diff in CE_{FC}**	**Findings** Bonferroni	LSD
H1: For **Simple-spatial** tasks, spatial (**graph**) information presentation formats result in **lower** cognitive effort than symbolic (**table**) formats.	-40.188**	Supported**	Supported***
H2: For **Simple-symbolic** tasks, symbolic (**table**) information presentation formats results in **lower** cognitive effort than spatial (**graph**) formats	-28.063	Not Supported	Supported***
H3: For **Complex-spatial** tasks, spatial (**graph**) information presentation formats result in **lower** cognitive effort than symbolic (**table**) formats	-101.031*	Supported*	Supported***
H4: For **Complex-symbolic** tasks, symbolic (**table**) information presentation formats result in **lower** cognitive effort than spatial (**graph**) formats.	19.500	Not Supported	Not Supported

*Sig <0.10 **Sig<0.05***Sig<0.01

Table 37: H1-H4 Summary (CE_{FC}) - Study #2

5.2.1.3 Results – Cognitive Effort measured through Self-Reported Cognitive Effort (CE_{SR2})

Although study #2 was primarily designed to evaluate the hypothesized impact on and of physiologically measured cognitive effort (CE_{FD} and CE_{FC}), data was collected on CE_{SR2} as in study #1.

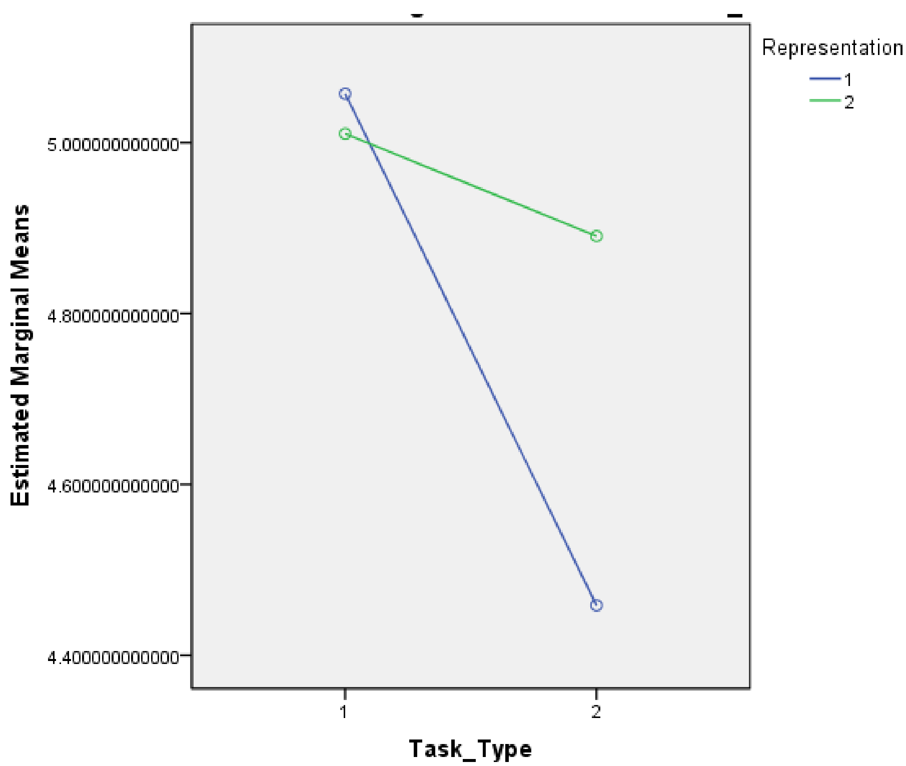
The Analysis of Variance (Table 38) showed an impact of the main effect of Task Complexity ($F(1,31)= 62.171$; $p=0.001$; $\eta_p^2=0.667$), Task Type ($F(1,31)= 10.383$; $p=0.003$; $\eta_p^2=0.251$) as well as the interaction effect of Task Type * Representation ($F(1,31)= 7.710$, $p=0.003$, $\eta_p^2=0.251$) . It should be noted that main effect of Representation ($F(1,31)= 2.377$, $p=0.065$, $\eta_p^2=0.105$) and interaction effects of Task_Complexity * Representation and Task_Complexity * Task_Type were approaching significance ($p=0.094$, and $p=0.139$).

Source	df	Mean Square	F	Sig.	P. Eta Squared	Obs. Power[a]
Task Complexity	1	68.063	62.171	.000	.667	1.000
Task Type	1	8.266	10.383	.003	.251	.877
Representation	1	2.377	3.651	.065	.105	.457
Task Complexity * Task Type	1	1.891	2.980	.094	.088	.387
Task Complexity * Representation	1	1.460	3.941	.056	.113	.486
Task Type * Representation	1	3.674	7.710	.009	.199	.767
Task Complexity * Task Type * Representation	1	1.563	2.301	.139	.069	.312
Subjects	31					
Error	217					
Total	255					

Table 38: ANOVA (CE_{SR2}) Results - Study #2

As in the case of $CE_{FC,}$ the impact of three way interaction between all three factors Task Complexity * Task Type * Representation on CE_{SR2} was not significant. However, since CFT and CFT-supported Hypotheses 1 through 4 do suggest interaction between Task Type and Representation, the interaction between those two treatments warrants closer understanding. Figure 15 shows how interaction effect between Task Type (1=Spatial, 2=Symbolic) and Representation (1=Table, 2=Graph), influences larger difference in CE_{SR2} for symbolic tasks while for spatial tasks CE_{SR2} difference is minimal (and in different direction). Figure 15 shows, as expected by CFT and H2 and H4, for symbolic tasks, users experienced lower CE_{SR2} when using tables over graphs.

Figure 15: Task Type * Representation (CE_{SR2}) Interaction



In order to understand whether the mean difference in CE_{SR} between Table and Graph was significant for only simple (H2) or complex (H4) task or both of them, a pairwise comparison of mean differences between experimental cells was completed

Task Complexity	Task Type	Format	Cell	Mean	Std.	N
Simple	Spatial	Graph	1	4.458	1.113	32
		Table	2	4.406	1.063	32
	Symbolic	Graph	3	3.875	1.431	32
		Table	4	4.615	1.262	32
Complex	Spatial	Graph	5	5.656	.870	32
		Table	6	5.615	.999	32
	Symbolic	Graph	7	5.042	1.063	32
		Table	8	5.167	1.023	32

Table 39: Descriptive Statistics - Study #2 - CE_{SR2}

Pairwise comparison mean difference (See Table 39 for descriptive statistics and Table 40 for mean differences) between Simple-Symbolic task – Table (Cell 3; M=3.875; SD=1.063) and Simple-Symbolic task – Graph (Cell 4; M=4.615; SD=1.262) of --.740 (SD=0.220) was significant (p=0.059) and in expected direction therefore *H2 was supported*. Comparison of CE_{SR} mean differences for Complex version of Spatial tasks (between Complex-Symbolic task – Table (Cell 7; M=5.042; SD=1.063) and Complex-Symbolic task – Graph (Cell 8; M=5.467; SD=1.023)) of -.125 (SD=0.154) was not significant (p= 1.000) and therefore *H4 was not supported*. To ensure that lack of statistical significance for Symbolic task is not due to Simple and Complex versions' impact on CE_{SR2} cancelling each other, a pairwise comparison of CE_{SR} mean difference between

Simple-Spatial task – Graph (Cell 2; M=4.406; SD=1.063) and Simple-Spatial task – Table (Cell 1; M=4.458; SD=1.113) of -0.052 (SD=0.175) and CE_{SR2} mean difference between Complex-Spatial task – Graph (Cell 6; M=5.615; SD=0.999) and Complex-Spatial task – Table (Cell 5; M=5.656; SD=0.870) of -0.042 (SD=0.183) was evaluated. Both were not significant (p=1.000) therefore *H1 and H3 were not supported*.

(I) Cells	(J) Cells	Mean Difference (I-J)	Std. Error	Sig.[a]	90% Confidence Interval for Difference[a] Lower Bound	Upper Bound
2	1	-.052	.175	1.000	-.603	.499
3	4	-.740*	.220	.059	-1.434	-.045
6	5	-.042	.183	1.000	-.617	.534
7	8	-.125	.154	1.000	-.610	.360

Based on estimated marginal means

a. Adjustment for multiple comparisons: Bonferroni.

*. The mean difference is significant at the .10 level.

Table 40: Pairwise Comparisons (CE_{SR2}) - Study #2

Table 41 summarizes findings on the hypothesized impact of Task Type and Representation fit on subjects' self-reported cognitive effort.

Hypotheses 1 - 4	**Cells**	**Cell Mean Diff in CE_{SR2}**	**Findings** Bonferroni	LSD
H1: For **Simple-spatial** tasks, spatial (**graph**) information presentation formats result in **lower** cognitive effort than symbolic (**table**) formats.	2 vs 1	-.052	Not Supported	Not Supported
H2: For **Simple-symbolic** tasks, symbolic (**table**) information presentation formats results in **lower** cognitive effort than spatial (**graph**) formats	3 vs 4	-.740	Supported*	Supported***
H3: For **Complex-spatial** tasks, spatial (**graph**) information presentation formats result in **lower** cognitive effort than symbolic (**table**) formats	6 vs 5	-.042	Not Supported	Not Supported
H4: For **Complex-symbolic** tasks, symbolic (**table**) information presentation formats result in **lower** cognitive effort than spatial (**graph**) formats.	7 vs 8	-.125	Not Supported	Not Supported

*Sig <0.10 **Sig<0.05***Sig<0.01

Table 41: H1-H4 Summary (CE_{SR2}) - Study #2

Table 42 offers combined results for H1 – H4 for Study #1 and Study #2 and provides an overview of hypothesized relationships across three measures of cognitive effort.

Hypotheses 1 - 4	**CE_{FD}**	**CF_{FC}**	**CF_{SR2}**	**CF_{SR1}**
H1: For **Simple-spatial** tasks, spatial (**graph**) information presentation formats result in **lower** cognitive effort than symbolic (**table**) formats.	-.019*	-40.188**	-.052	.083
H2: For **Simple-symbolic** tasks, symbolic (**table**) information presentation formats results in **lower** cognitive effort than spatial (**graph**) formats	-.031**	-28.063	-.740*	-.338
H3: For **Complex-spatial** tasks, spatial (**graph**) information presentation formats result in **lower** cognitive effort than symbolic (**table**) formats	-.015**	-101.031*	-.042	-.368
H4: For **Complex-symbolic** tasks, symbolic (**table**) information presentation formats result in **lower** cognitive effort than spatial (**graph**) formats.	.009	19.500	-.125	-.377

*Sig <0.10 **Sig<0.05

Table 42: H1-H4 Summary – Study #1 and #2

5.2.2 Study #2 - Hypothesis 5

Multiple regression tests were conducted to test H5 where expectation was for the relationship between cognitive effort and time (H5) to be moderated by the level of participants' Need for Cognition. H5 was tested using all three measures of cognitive effort ($CE_{FD,}$ CE_{FC} and CE_{SR}). All three measures of cognitive effort and NFC were mean centered before using them as interaction in the regression.

Using CE_{FD} and NFC score and their interaction (mean centered), regression model (A) found statistically significant impact of CE_{FD} on Time but no effect of NFC nor the interaction between the two was detected (Adjusted R Squre=1.6%, $F(3, 252)=2.418$, $p=0.067$). Therefore hypothesized impact of CE_{FD} * NFC on Time (H5) was not supported.

Regression model (B) using CE_{FC} and NFC score and their interaction (mean centered) on Time found statistically significant direct impact of CE_{FC} on Time but no direct effect of NFC nor the interaction between the two was detected (Adjusted R Squre=94.4%, $F(3, 252)=1446.752$, $p<0.01$). Therefore hypothesized impact of CE_{FD} * NFC on Time (H5) was not supported.

Lastly, regression model (C) using CE_{SR2} and NFC score and their interaction (mean centered) on Time found statistically significant direct impact of CE_{SR2} on Time but no direct effect of NFC nor the interaction between the two was detected (Adjusted R Square=16.9%, $F(3,252)=18.329$, $p<0.01$). Therefore hypothesized impact of CE_{SR2} * NFC on Time (H5) was not supported.

(A)		(B)		(C)	
Constant	118.706*** (5.930)	Constant	118.896*** (1.408)	Constant	118.942*** (5.445)
CE_{FD}	322.947** (130.772)	CE_{FC}	.454*** (007)	CE_{SR2}	32.297*** (4.416)
NFC	-2.259 (8.996)	NFC	-.457 (2.173)	NFC	-2.589 (8.378)
CE_{FD} x NFC	-171.868 (209.241)	CE_{FC} x NFC	-.0171 (.012)	CE_{SR2}xNFC	-.751 (6.709)
R Square	0.028		0.945		0.178
Adjusted R Square	0.016		0.944		0.169
No of Observations	256				

Standard Error are noted in parenthesis
*,**,*** indicates significance at the 90%, 95% and 99% level, respectively

Table 43: H5 Regression - Study #2[9]

Table 44 provides a summary for hypotheses 5 using for all three measures of cognitive effort. Given lack of support for H5 hypothesis, mediation test for cognitive effort * NFC interaction was not conducted.

Hypothesis	CE_{FD}	CE_{FC}	CE_{SR2}
H5: Increase in Cognitive effort increases the amount of time required for a decision and this relationship is amplified with increase in individual's Need for Cognition	Not Supported	Not Supported	Not Supported

Table 44: H5 Summary - Study #2

[9] Regression tests were also completed with inclusion of Domain Knowledge. Domain knowledge was significant in tests using CE_{SR2} and CE_{FD}. In case of CE_{SR2}, adjusted R-square increased from 17% to 20%, in case of CE_{FD} adjusted R-Square increased from 1.6% to 4%. In regression model with Domain knowledge, however, the significance and relative impact of cognitive effort, NFC and its interaction was unchanged relative to regression models in Table 43.

5.2.3 Study #2 - Hypothesis 6

Multiple regression tests (Table 45) were conducted to test H6 where expectation was for the relationship between cognitive effort and accuracy to be moderated by the level of participants Need for Cognition. H6 was also tested using all three measures of cognitive effort (CE_{FD}, CE_{FC} and CE_{SR}). All three measures of cognitive effort and NFC were mean centered before using them in the regression as interaction.

The overall model testing the impact of CE_{FD} and NFC on Accuracy was not significant ($F(3,252)=1.344$, $p=0.261$) with adjusted R Square=0.3%. None of the individual variables were significant, therefore, hypothesized impact of CE_{FD} * NFC on Accuracy (H6) was not supported.

The overall model testing the impact of CE_{Fc} and NFC on Accuracy was significant ($F(3, 252)=3.588$, $p=0.014$) with adjusted R Square=3%. Direct impact of CE_{FC} on Accuracy was significant but no direct effect of NFC nor the interaction between the two was detected. Therefore, hypothesized impact of CE_{Fc} * NFC on Accuracy (H6) was not supported.

The overall model testing the impact of CE_{SR2} and NFC on Accuracy was significant at 0.1 ($F(3, 252)=2.168$, $p=0.09$) with adjusted R Square=2%. Direct impact of CE_{SR2} on Accuracy was significant but no direct effect of NFC nor the interaction between the two was detected. Therefore, hypothesized impact of CE_{SR2} * NFC on Accuracy (H6) was not supported.

(A)		(B)		(C)	
Constant	.906 (.088)	Constant	.999 (.058)	Constant	1.035 (.066)
CE_{FD}	.186 (.654)	CE_{FC}	-.001*** (.0001)	CE_{SR2}	-.015** (.006)
NFC	-.006 (.12)	NFC	-.009 (.012)	NFC	--.008 (.012)
CE_{FD} x NFC	-0.475 (.027)	CE_{FC} x NFC	.000 (.000)	CE_{SR2}x NFC	-.007 (.009)
R Square	0.016		0.041		0.025
Adjusted R Square	0.004		0.03		0.014
No of Observations	256				

Standard Error are noted in parenthesis
,* indicates significance at the 90%, 95% and 99% level, respectively

Table 45: H6 Regression - Study #2[10]

Table 43 provides a summary for hypotheses 6 using for all three measures of cognitive effort. Given lack of support for H6 hypothesis, mediation test for cognitive effort * NFC interaction was not conducted.

Hypothesis	CE_{FD}	CE_{FC}	CE_{SR2}
H6: Increase in Cognitive effort negatively impacts decision accuracy and this relationship is amplified with decrease in individual's Need for Cognition	Not Supported	Not Supported	Not Supported

Table 46: H6 Summary - Study #2

[10] A regression for each measure of cognitive effort was also tested with Domain Knowledge as first variable in each regression test. Domain Knowledge was not significant in any of those three tests.

CHAPTER VI

6. DISCUSSON AND IMPLICATIONS

6.1 Discussion

This research was designed to examine how match between task type and representation format impacts cognitive effort and how cognitive effort impacts decision performance; time and accuracy. The research was based on cognitive fit theory and CFT-based IS literature that suggested a direct link between task type and presentation format. According to the original CFT, cognitive fit between the problem representation (presentation format) and the problem-solving task occurs "when the problem-solving aids (problem representation among them) support the task strategies required to perform that task" (Vessey, 1991a), 220). Therefore, matching the representation to the task leads to use of similar problem-solving processes and form a match with formulated mental representation for task solution. In other words, individuals develop mental representation of the task and adopt decision processes based on the task and the presentation of task information (Vessey, 1991a; Vessey & Galletta, 1991). As a result, the performance depends upon the fit between information presentation, task, and decision processes used by the decision maker. CFT proposes that cognitive effort is the mechanism being impacted by the fit and variable that drives decision making performance.

As such, this study is the first to examine in controlled setting and measure directly how match between task type and representation format impacts cognitive effort. Study #1 was designed to evaluate how users' perception of cognitive effort is being impacted by task type and representation match where the perception of cognitive effort was measured through self-reported answers. The results show that, given tasks used in the research, users generally do not appear to perceive significant change in self-reported cognitive effort regardless of the presence or absence of cognitive fit. Contrary to expectations, regardless of the complexity of the task, the match between task type (spatial, symbolic) and representation did not significantly impact decision makers' perception (self-reported) of cognitive effort. Instead, post-hoc analysis indicated that cognitive effort is primarily driven by complexity of the task itself, where variance explained in self-reported cognitive (as captured through η_p^2) is significantly larger for task complexity than for other any variable (task type, representation) and their interactions.

For example, when comparing tasks we see that users do perceive simple-spatial task (Cell 1 and Cell 2) and simple-symbolic task (Cell 3 and Cell 4) resulting in lower cognitive effort than either complex task, regardless of the presentation format. Some of this result is undoubtedly directly linked to specific tasks used in this experiment and result may vary with changes in tasks. Another potential explanation for the importance of task complexity may reside in our design and analysis method where statistical significance was set to a more restrictive adjustment (Bonferroni). By focusing only on pairs of cells within same task the research finds that significant difference in self-reported cognitive effort for both complex tasks (H3 and H4) while for simple symbolic task (H2) it was approaching significance (0.11). In other words, study focused on only complex or only simple task may be able to detect the theorized impact of task type/representation fit on self-reported cognitive effort. Study #2 generally confirmed the dominance of task complexity on decision makers' self-reported cognitive effort. However, in study #2 differences in effort were detected beyond complexity (for simple-symbolic task) and it could be explained partially by difference in design between two studies and the ability to remove some within subject variance in study #2.

Given these findings it was particularly useful to evaluate if our perception of cognitive effort is different from our physiological indicators of cognitive effort. Therefore, study #2 was primarily designed to assess the physiological experience of cognitive effort, namely eye-movement behavior through eye-tracking technology. As in the case of self-reported measure of cognitive effort, this is the first study to assess in controlled environment and through CFT lens how task type and representation match impact physiological experience of effort. More in line with expectations and CFT, study #2 suggests that the impact of combined effect of task type and representation is detected beyond the individual effects of task complexity, task type or representation and that detection ability is greater than in self-reported measure of cognitive effort. In the case of average fixation duration, the study found that in all cases except complex-symbolic task, users do experience meaningful change in cognitive effort and attention based on the condition of fit between task type and representation. In other words, the impact on cognitive effort cannot be fully explained by only change in task complexity as it needs to also account whether there is a lack or presence of task type and representation fit.

These findings are in line with expectations as average fixation duration captures the attention and the focus of decision maker's pupil on a particular point. If representation makes it hard for user to assess the meaning of a particular area of representation, he/she needs to focus more intently and more frequently to understand information. This will lead to longer average fixation duration and more of them, as in the instance of simple –spatial task users fixated on average 19ms longer when assessing information with tables (lack of cognitive fit) over when assessing information with graphs (presence of cognitive fit). At the same time, those same users experienced, on average, over 40 more fixations. In other words, during simple-spatial tasks and when using graphical representations users experienced less intense effort (fixation duration) and in less frequency (fixation count). In the instance of simple-symbolic task and when using tables (fit) users exhibited 31ms shorted fixation durations compare to fixation durations when using graphs (no fit). Although same users did exhibit smaller number of fixations, the results lacked statistical significance. It is interesting to note that in the case of simple-symbolic task, users did indicated lower self-reported cognitive effort. It is also important to note that these statistically significant findings were detected during relatively short period of time (simple task required less time), further enhancing the power of the finding. In summary, the results indicate strong support for the notion that in simple tasks, task-representation fit is important and when users are provided with graphical representations performing symbolic tasks or tabular representations performing spatial task (i.e lack of fit), they experience increase in cognitive effort relative to when representations match the mental model to solve the problem.

For complex tasks, the findings offer less clarity. For complex-spatial task, users exhibited 15ms shorter fixation durations when using tables (fit) over fixation durations when using graphs (no fit) while at the same time exhibiting on average about 100 fewer fixations. As in simple-spatial task, during complex-spatial tasks and when using graphical representations, users experienced less intense effort (fixation duration) and had smaller frequency (fixation count). However, for complex-symbolic tasks task-representation fit had no significant implication on cognitive effort. One explanation may reside in a possibility that for spatial tasks human's limited memory capacity (Miller, 1956) makes tabular presentations very difficult to use yet users are willing to extend/experience cognitive effort given assurance that correct answer is possible given sufficient effort, while for graphical representation, especially complex one that certainty is missing due to our low ability to precisely estimate graphs. Exhibited behavior during experiment aligns with that explanation as users during spatial task and when presented with tabular format focused on calculating on paper/out loud, which resulted in more fixations and longer fixations, and perception of effort.

The same users, when facing complex-symbolic problem but now with graphical presentation had no direct ability to calculate precisely values and at some point potentially recognized no value in further evaluation. In short, they decided to optimize resulting in less effort. This may hint at suggestion of a trade-off that users make with complex tasks where they are willing to extend/experience more effort if it provides them with more confidence in an answer. This notion has been noted in consumer research that consumers may avoid particular choice selection process because it requires a significant effort and opt to select to use an easier process instead (Cooper-Martin, 1994), a decision maker may avoid a complex decision making process and in favor of an easier one. This preference for cognitive effort minimization may result in suboptimal decisions. The lack of clarity in instances of complex tasks has been noted in prior literature where appropriateness of CFT to explain user performance has been questioned by others. This research suggests a need to further explore and better understand factors influencing effort during more complex symbolic tasks.

Hypotheses 5 and 6 evaluated the role of cognitive effort and NFC on decision performance measured through time and accuracy. No hypothesized moderating effect of NFC was found. One possible explanation is that tasks themselves, although varied in complexity and difficulty never reached a threshold at which users had the need to continue effortful activity. Related explanation may stem from the fact that all users self-reported high level of motivation to perform well during experiments. Combined with monetary and class credit motivation, the ability to detect hypothesized impact of NFC may be difficult.

Cognitive effort, however, did have an effect on time in both studies and for all measures of cognitive effort. Average fixation duration, together with NFC, was able to explain limited amount of variance in Time (1.6%) and unable to explain variance in Accuracy. Although fixation count explained 94% of variance in Time, high correlation between these variables appear to indicate that they both measure the same phenomenon. Fixation count also explained 3% of variance in Accuracy, while Average Fixation Duration was not significant. Self-reported cognitive effort explained 13.2% variance in Time in study#1 and 16.9% of variance in Time in study #2. On the other hand, self-reported cognitive effort explained 2.4% of variance in Accuracy in study #1 and 1.4% in study #2. It needs to be noted that results for survey #1 and #2 as it relates to CE_{SR} are very consistent in terms of impact on both time and accuracy.

This research suggests that users' perception of cognitive effort will influence decision performance (namely time) more than physiological indicators of how intensive (average fixation duration) or extensive (fixation count) is the effort. Given this study's lack of ability to show great influence of task-representation fit on self-reported cognitive effort (only in simple-symbolic task) and provided evidence of significant role of task complexity, a potential conclusion may be made that in tested context, task complexity has stronger influence on decision performance especially in a scenario where users are facing task and representation in which users believe that extra effort will lead to correct answer, over a scenario when they decide to optimize effort with outcome accuracy.

The findings relative to the impact of task complexity, and to some degree task type, indicates that it is important to understand what other factors impact users' perception of cognitive effort. The research suggest that focus on only task – representation fit will be less effective than deploying combined focus by both simplifying tasks and providing appropriate representation.

6.2 Research Implications

Beyond the immediate context of the study, this research offers four important and closely linked research implications. First, this is, to the best of my knowledge, the first study that directly measures cognitive effort in the context of business information presentation and cognitive fit theory literature. This study is the first to examine in controlled setting and measure directly how match between task type and representation format impacts cognitive effort. Cognitive Fit Theory is a dominant and influential lens through which IS community investigated appropriateness of data presentation across contexts, tasks and domains. Given the significant theoretical role of users' cognitive effort in explaining CFT-based literature results, the lack of more nuanced and direct empirical support for the notion of cognitive effort represented an opportunity for this research. Confirmation of the impact of task-representation fit on cognitive effort is a first, yet important step for CFT-based literature stream. While it provides validation of task-representation fit, it does suggest attention is needed to ensure that cognitive effort is not driven by factor other than the theorized fit, such as varied perception of complexity of interaction of complexity with task type. This further suggests that the role of cognitive effort needs to be better understood before further extensions and adaptations of existing cognition-based theories are offered to domains outside of original theory-building environment, as is has been already done in a number of instances. The original environment that gave rise to the dominant viewpoint centered on Cognitive Fit Theory consisted of empirical research that compared decision performance in simple tasks across tabular and graphical presentation formats. This was an example of grounded theory building and, as such could be significantly dependent on the context and environment that was created in. Hence, I suggest that the extension of theory to other domains could be premature if the underlying mechanism, cognitive effort, is not understood and measured in an improved manner. This research is a step in that direction.

Second and closely linked to the fist implication, this research informs the IS community of multidimensionality of cognitive effort construct while validating psychology and decision making cognitive effort focused literature. In addition to being the first study that directly measures cognitive effort in the context of business information presentation and cognitive fit theory literature, this research offers the suggestion that oversimplification of cognitive effort may cause for important results to be misunderstood or dismissed. The study provides support that in some contexts users experience cognitive effort differently, both as a perception and physiologically. Even within those two categories this research finds difference in how intensive that cognitive effort is (average fixation duration) vs how extensive it is (time or fixation count). A component of CFT-based research could build from initial findings of this study to evaluate implications and context of each dimension of cognitive effort.

Third, this research finds difference under certain conditions between how system users self-report (perceive) cognitive effort and what they actually physiologically experience. In the context of this study no significant correlation was detected between average fixation duration and self-reported cognitive effort, however a correlation of $r=0.45$ was detected between fixation count and self-reported cognitive effort. Hence, this distinction between perceived and physiological measure is particularly important for IS discipline as IS discipline often relies on constructs based on users perceptions of systems. This research suggest that they both need to be considered and studies that incorporate both measurements of effort and user engagement may find important contributions to the IS field.

Fourth, this research introduces eye-tracking as a viable tool for research of user behavior in DSS and Business Information Visualization research areas of IS. While eye-tracking technology has been extensively used in consumer focused web and interface design research, as well as in non-IS field such as Marketing, Communication, and the Medical field, surprisingly little research has been conducted in the fields of Decision Support Systems/Business Intelligence and Business Information Visualization. Measures such as average fixation duration, fixation count, fixation rate, and areas of interest are just some of the eye-tracking based measures that offer great potential in improving our understanding of how certain design features impact the use of DSS and Business Intelligence tools. Furthermore, they may provide a more objective assessment of wide-array of new and often questionable presentation formats currently used or pushed by both DSS/BI vendors and academia.

6.3 Practical Implications

In practical context of data representation tools, executives, managers and knowledge workers make decisions daily and frequently. Their decision making performance is important for their professional and organizational success. Since organizations strive to make decisions that are rooted in data and information, it is not surprising that data representation is critical in the ability to support decision making performance. Given ubiquity of data representations in business decision making, improvements in understanding factors influencing users' cognitive effort and subsequent decision performance could offer significant practical value.

Specifically, this research suggests the need to not only focus on representation format but consider both jointly and independently the implication of complexity, task type and representation. In the age of Big Data and complex problems, information visualization of often perceived a way to enable both reduction of information complexity and uncertainty. In a quest to discover new knowledge, see the 'unseen' and occasionally visually impress the audience, vendors and report designers occasionally are more focused on visualization features rather than on data itself resulting in a practice labeled ‘chartjunk’ where instead of reduction of complexity and uncertainty the effect may be exactly the opposite. This research provides evidence that even when using the best practices in table and graph design, if deployed against inappropriate task they may increase users’ cognitive effort. If that mismatch is further amplified with bad design practices beyond format choice, one may expect to create even higher increase in users’ cognitive effort. Therefore, the findings in this research help information delivery professionals have greater understanding of how and through which relationships data representation impacts decision makers’ cognitive effort.

By increasing our understanding of cognitive effort role in BIV, this research may offer a new and alternate way for BI professionals in the process of selecting appropriate presentation formats, features and capabilities to deploy to reduce complexity and improve task- representation fit. Given the importance of task complexity, this research suggests that part of effective BI information delivery platform is not only ensuring the right format but also presenting it in way that it reduces perceived complexity of the problem.

Similarly, data visualization and dashboard vendors can leverage the measures of cognitive effort used in this study as a key component and feedback input to their development cycle. The ability to understand and focus on how new product capabilities, modifications and enhancements impact users’ cognitive effort will offer a way to evaluate and prioritize product feature changes.

In summary, research question focused on understanding and better measurement of the implications of representation design on users' cognitive effort can extend our current knowledge in BIV as an important component of BI/DSS and decision making process. As business users depend on data for informed decision making, this data is packaged and presented to them visually; therefore, the understanding of the role of business information visualization on cognitive effort and decision performance allows practitioners to learn and implement best practices centered on enabling desired effect of visualization on users' cognitive effort.

CHAPTER VII

7. LIMITATIONS AND FUTURE RESEARCH

Like all research involving eye-tracking technology, this research has some limitations, both from resource and technical perspective. First, both study #1 and study #2 were conducted in a laboratory environment which does not accurately represent real-life situations of report usage and decision-making. For example in both studies users evaluated problem and data representations on single and identical screens. In non-laboratory setting, users often view and analyze information on multiple media from paper reports to tablets and smartphones. Therefore, it would be interesting to evaluate how and if different media formats impact identified relationship in this research.

Second, while every attempt was made to minimize the influence of eye-tracking equipment, ranging from choice of remote eye-tracker (vs head-mounted eye tracker) to a script that carefully concealed exact purpose of eye-tracking technology, the influence of some limitations such as minimal limitations to viewing angle accuracy and recording speed of the eye-tracker need to be taken into consideration when evaluating the results.

Third, the use of students is a practical limitation, even as prior research has argued that is does not necessarily limit the generalizability of the results (Campbell, 1986; Dipboye & Flannigan). Some difference in sample between study #1 and study #2 was evident while the reported similarity of results provides further evidence that the use of students does not completely limit the generalizability of the results. However, repeating these experiments across different segments of population may reveal some new insights.

Fourth, the performance difference between representation formats may be partly caused by other factors than task complexity and task type which is inherent in any research involving fit. Every effort was made that each representation format deploys best practices in information presentation. Other research may evaluate and test model with representation features not present in this research.

Fifth, tasks and context (Financial and Managerial Accounting) was selected purposefully. It was selected due to its ubiquity in general business setting and the knowledge of those basic concepts used in this research represents general knowledge regardless of participants' business field. Other research may consider focusing on tasks in more specific business discipline such as finance (for example, more complicated activity based costing tasks), marketing (analysis of customer marketing campaign), operations management (inventory level analysis), or human resources (employee turnover) for example and evaluate the research with appropriate population. Discipline specific factors may emerge to further enhance the practical benefit of this research.

Sixth, Study #1 deployed three-way between subject ANOVA test to evaluate the impact of hypothesized task-representation fit on self-reported cognitive effort. In actual data collection, however, all subjects performed all four task complexity and task type experimental cells and were randomly assigned representation (table or graph) for each task separately. Because of inability to treat Representation factor as between-subject, this data collection method prevented effective mixed design ANOVA testing. In study #2 where, however, data collection was therefore modified and designed so that all subjects performed all 8 cells, thus enabling appropriate and effective within-subject ANOVA testing of H1-H4.

Beyond suggested research stemming from limitations of this study, there are other future issues. Given cognitive effort's influence on performance, what are its other antecedents and potential moderators on its influence on performance? Are there other important measures of performance, beyond accuracy and time, such as creativity, insight generation, and confidence? Is there a link between cognitive effort and mood and emotions in IS context? Both technology adoption and continued use streams of research may benefit in enhancing the understanding of how task-representation fit and cognitive effort influence important constructs such as ease of use and perceived usefulness of the system.

Lastly, Information Visualization field continues to introduce new ways to visually present increasingly complex and large data sets. Measures of cognitive effort could offer an avenue to evaluate the benefits and drawbacks of those visualization formats and their features. For example, what is the cost in cognitive effort when comparing 2D vs 3D visualizations such as bar or pie charts? How does introduction of color in visualization influence users' cognitive effort? How does data legend and its position influence users experience with visualization? How do experience and perceived cognitive efforts influence users' perception of complexity and uncertainty of visually displayed information? How does location of objects in a dashboard influence users visual path and resulting cognitive effort?

CHAPTER VIII

8. CONCLUSION

The goal of the research was to further explore and expand our understanding of how data representation impacts decision performance by focusing on cognitive effort along with other relevant, theoretically supported variables such as task, presentation format and user characteristics, namely tendency to engage in and enjoy effortful cognitive activity. This research started with a number of research questions. First, does data presentation format impact cognitive effort? Presented research suggests that it does and it does so in a nuanced way. In both studies, subjects do not experience significant change in self-reported cognitive effort based on the representation format they were provided to solve the task. They do, however, experience different levels of cognitive effort when those representation formats are combined with certain tasks, which leads to the second research question.

Second research question asks whether task characteristic impact cognitive effort? The research clearly found that task complexity is an important factor influencing cognitive effort. Evidence of that could be found in pairwise comparisons between means of measures of cognitive effort between cells of differing levels of complexity. On the other hand, task type (spatial or symbolic) characteristic does appear to impact cognitive effort through interaction with representation format. This effect is especially pronounced when measuring cognitive effort though average fixation duration where in all tasks but complex-spatial validated CFT. As a result, this research found that combined effect of task complexity, task type and representation influences cognitive effort measured through eye-tracking technology. Above finding allows me to answer the third research question - is there interplay between data presentation format and task characteristic on users' cognitive effort? In line with CFT, this research found that in some tasks there is theory suggested impact of match between task type and representation on cognitive effort. While self-reported measure was able to detect the combined effect of task type and representation for simple-symbolic task in study #2 and approached significance for two complex tasks in study #1, it appears that our capacity to perceive change in cognitive effort was mostly driven by task complexity. Two eye-tracking based measures of cognitive effort, on the other hand, behaved more in line with CFT as they were able to detect the impact of task-representation fit in all tasks except complex-symbolic.

An important assumption of CFT is that decision performance (time and accuracy) is driven by cognitive effort. Hence, fourth research question asks whether there is an impact of cognitive effort on decision performance. This is the first research effort using CFT theoretical lens that measured and confirmed that cognitive effort is influencing decision performance – both as self-reported and physiological measured phenomenon. The research suggests, in context of this study, that self-reported cognitive effort explains more variance in decision time than in decision accuracy, both after accounting for decision makers' level of domain knowledge. Furthermore, the research offers insight that cognitive effort induced through task-representation fit state may not be as valuable predictor of decision accuracy as suggested by CFT. The analysis of cognitive effort's impact on performance also revealed that fixation count and time measure the same phenomenon, while the impact of fixation duration is present but smaller than the impact of self-reported cognitive effort..

Fifth research question asks whether there is an impact of user characteristics, namely NFC on cognitive effort and decision performance. Expected combined effect of NFC and cognitive effort on decision performance was not detected in either study. Similarly, no significant effect of Need for Cognition on measures of cognitive effort was found either. In study #1, Need for Cognition did explain 2% of variance in time it took subjects to complete the task, however that effect was absent in study #2. Therefore, the results are, at best, inconclusive and more research is warranted to better understand both NFC and potentially other user characteristics as it pertains to its role in cognitive effort/decision performance relationship.

Last research question asks if there are effective ways of measuring cognitive effort in the context of this research. One of the major contributions of this research is the evidence of multiple effective ways of measuring cognitive effort in the context of business information visualization. The research found that both self-reported and eye-tracking based measures of cognitive effort add valuable insight to our understanding of the role of fit between task and representation as well as how cognitive effort impacts ultimate decision performance. The research also confirms multidimensional nature of cognitive effort with potentially different impacts on different performance outcomes. These are encouraging findings. Other novel ways of measuring cognitive effort should be considered as they may reveal important and currently unknown factors that may influence decision making process beyond task-representation match.

In conclusion, a major goal of DSS and BI systems is to aid decision makers in their decision performance by reducing effort. One critical part of those systems is their data representation component of visually intensive applications such as dashboards and data visualization. Initial findings suggests that having greater understanding of (i) how and through which relationships data representation impacts decision makers' cognitive effort, and (ii) how cognitive effort impacts decision performance is a promising avenue for meaningful contribution to both research and practice. This research is a good step in that direction.

APPENDIX

APPENDIX – Study 1 – LSD –based results

Pairwise Comparisons

Dependent Variable:COG_EFFORT_SR

(I) Cell_id	(J) Cell_id	Mean Difference (I-J)	Std. Error	Sig.[a]	90% Confidence Interval for Difference[a]	
					Lower Bound	Upper Bound
1	2	-.083	.212	.694	-.433	.266
	3	.118	.212	.579	-.232	.467
	4	-.221	.212	.298	-.570	.129
	5	-1.000*	.212	.000	-1.349	-.651
	6	-.632*	.212	.003	-.982	-.283
	7	-.284	.212	.180	-.634	.065
	8	-.662*	.212	.002	-1.011	-.312
2	**1**	**.083**	**.212**	**.694**	**-.266**	**.433**
	3	.201	.212	.343	-.149	.550
	4	-.137	.212	.517	-.487	.212
	5	-.917*	.212	.000	-1.266	-.567
	6	-.549*	.212	.010	-.899	-.200
	7	-.201	.212	.343	-.550	.149
	8	-.578*	.212	.007	-.928	-.229
3	1	-.118	.212	.579	-.467	.232
	2	-.201	.212	.343	-.550	.149
	4	**-.338**	**.212**	**.111**	**-.688**	**.011**
	5	-1.118*	.212	.000	-1.467	-.768
	6	-.750*	.212	.000	-1.099	-.401
	7	-.402*	.212	.059	-.751	-.052
	8	-.779*	.212	.000	-1.129	-.430
4	1	.221	.212	.298	-.129	.570
	2	.137	.212	.517	-.212	.487
	3	.338	.212	.111	-.011	.688
	5	-.779*	.212	.000	-1.129	-.430
	6	-.412*	.212	.053	-.761	-.062
	7	-.064	.212	.764	-.413	.286
	8	-.441*	.212	.038	-.791	-.092
5	1	1.000*	.212	.000	.651	1.349
	2	.917*	.212	.000	.567	1.266
	3	1.118*	.212	.000	.768	1.467
	4	.779*	.212	.000	.430	1.129
	6	.368*	.212	.084	.018	.717
	7	.716*	.212	.001	.366	1.065
	8	.338	.212	.111	-.011	.688
6	1	.632*	.212	.003	.283	.982
	2	.549*	.212	.010	.200	.899
	3	.750*	.212	.000	.401	1.099

	4	.412*	.212	.053	.062	.761
	5	**-.368***	**.212**	**.084**	**-.717**	**-.018**
	7	.348	.212	.101	-.001	.698
	8	-.029	.212	.890	-.379	.320
7	1	.284	.212	.180	-.065	.634
	2	.201	.212	.343	-.149	.550
	3	.402*	.212	.059	.052	.751
	4	.064	.212	.764	-.286	.413
	5	-.716*	.212	.001	-1.065	-.366
	6	-.348	.212	.101	-.698	.001
	8	**-.377***	**.212**	**.076**	**-.727**	**-.028**
8	1	.662*	.212	.002	.312	1.011
	2	.578*	.212	.007	.229	.928
	3	.779*	.212	.000	.430	1.129
	4	.441*	.212	.038	.092	.791
	5	-.338	.212	.111	-.688	.011
	6	.029	.212	.890	-.320	.379
	7	.377*	.212	.076	.028	.727

Based on estimated marginal means

a. Adjustment for multiple comparisons: Least Significant Difference (equivalent to no adjustments).

*. The mean difference is significant at the 0.1 level.

Hypotheses 1 - 4	Cells	Cell Mean Diff in CE_{SR1}	Findings
H1: For **Simple-spatial** tasks, spatial (**graph)** information presentation formats result in **lower** cognitive effort than symbolic (**table**) formats.	2 vs 1	.083	Not Supported
H2: For **Simple-symbolic** tasks, symbolic (**table**) information presentation formats results in **lower** cognitive effort than spatial (**graph**) formats	3 vs 4	-.338	Not Supported
H3: For **Complex-spatial** tasks, spatial (**graph**) information presentation formats result in **lower** cognitive effort than symbolic (**table**) formats	6 vs 5	-.368*	Supported
H4: For **Complex-symbolic** tasks, symbolic (**table**) information presentation formats result in **lower** cognitive effort than spatial (**graph**) formats.	7 vs 8	-.377*	Supported

*Sig <0.10 **Sig<0.05

Monte Ahuja College of Business
Department of Computer & Information Science

Informed Consent Form – Study #1

Introduction
My name is Dinko Bačić and I am a doctoral student at CSU. I am conducting a study that attempts to collect information about factors contributing to quality and speed of judgment and decisions and it is an integral component of my doctoral dissertation. Thank you for volunteering to participate in this research.

Procedures
You will be asked a series of questions regarding your background, your attitude, followed by questions measuring your level of accounting knowledge. Next, you will be presented with short accounting tasks. After the completion of each task you will be asked to indicate your agreement with statements relative to your perception of the task. There is no time limit to this survey and answering all questions will take approximately 45 minutes or less. This questionnaire will be conducted with an online Qualtrics-created survey.

Risks/Discomforts
Risks are minimal for involvement in this study, i.e. risks do not exceed that of normal daily activities. Discomfort or inconvenience level is similar to the levels experienced by answering class related questions in class or class related computer lab assignment. Although we do not expect any harm to come upon any participants due to electronic malfunction of the computer, it is possible though extremely rare and uncommon.

Benefits
The list of benefits for participants is provided in the Compensation section of this form (discretionary extra academic credit and opportunity to win an additional $50 gift card). Furthermore, it is hoped that through your participation, researchers will learn more about which factors contributing to improved decision performance.

Confidentiality
All data obtained from participants will be kept confidential and will only be reported in an aggregate format (by reporting only combined results and never reporting individual ones). All questionnaires will be concealed, and no one other than then primary investigator and assistant researches listed below will have access to them. Once personal information used for academic credit and performance/participation award is communicated, the personal information will be deleted and not used in subsequent analysis. The data collected will be stored in the HIPPA-compliant, Qualtrics-secure database until it has been deleted by the primary investigator. The backup will be moved to official CSU server for 3 year period per IRB compliance.

Compensation

Participants may earn extra academic credit, at the discretion of their professors. Top 3 (three) participants will receive $50 gift card for competing tasks quickly and accurately. Task performance will be measured by decision of accuracy per unit of time.

Participation
Participation in this research study is completely voluntary. You have the right to withdraw at any time or refuse to participate entirely without jeopardy to your academic status, GPA or standing with the university. If you desire to withdraw, please close your internet browser and notify the principal investigator at this email: d.bacic@csuohio,edu. Or, if you prefer, inform the principal investigator as you leave.

Questions about the Research
If you have questions regarding this study, you may contact Dinko Bačić, at 216-513-4532, d.bacic@csuohio.edu.

Questions about your Rights as Research Participants
I understand that if I have any questions about my rights as a research subject I can contact for CSU's Institutional Review Board at (216) 687-3630

I have read, understood, and desire of my own free will to participate in this study.

SIGNITURE DATE

Monte Ahuja College of Business
Department of Computer & Information Science

Informed Consent Form - Study #2

Introduction
My name is Dinko Bačić and I am a doctoral student at CSU. I am conducting a study that attempts to collect information about factors contributing to quality and speed of judgment and decisions and it is an integral component of my doctoral dissertation. Thank you for volunteering to participate in this research.

Procedures
You will be asked a series of questions regarding your background, your attitude, followed by questions measuring you level of accounting knowledge. Next, you will be placed in front of a monitor with eye-tracker where you will be guided through 5-10 second process of calibration. Once calibration process is completed you will be presented with a problem/task and table(s) or graph(s) containing information needed to provide answer to the problem.. After the completion of each task you will be asked to indicate your agreement with statements relative to your perception of the task. There is no time limit to this study and answering all questions will take approximately 45-60 minutes or less. This first part (questionnaire) of the study will be conducted with an online Qualtrics-created survey. The second part (your answers regarding tasks) will be manually recorded by the investigator.

Risks/Discomforts
Risks are minimal for involvement in this study, i.e. risks do not exceed that of normal daily activities. Discomfort or inconvenience level is similar to the levels experienced by answering class related questions in class or class related computer lab assignment. Although we do not expect any harm to come upon any participants due to electronic malfunction of the computer, it is possible though extremely rare and uncommon.

Benefits
The list of benefits for participants is provided in the Compensation section of this form (extra academic credit, $10 gift card, and opportunity to win an additional $50 gift card. Furthermore, it is hoped that through your participation, researchers will learn more about which factors contributing to improved decision performance.

Confidentiality
All data obtained from participants will be kept confidential and will only be reported in an aggregate format (by reporting only combined results and never reporting individual ones). All questionnaires will be concealed, and no one other than then primary investigator and assistant researches listed below will have access to them. Once personal information used for academic credit and performance/participation award is communicated, the personal information will be deleted and not used in subsequent analysis. The data collected will be stored in the HIPPA-compliant, Qualtrics and Eyetracking -secure database until it has been deleted by the primary investigator. The backup will be moved to official CSU server for 3 year period per IRB compliance.

Compensation
Participants may earn extra academic credit, at the discretion of their professors. You will also be compensated for your time in the amount $10 (in the form of a gift card). Top 3 (three) participants will receive $50 gift card for competing tasks quickly and accurately. Task performance will be measured by decision of accuracy per unit of time.

Participation
Participation in this research study is completely voluntary. You have the right to withdraw at any time or refuse to participate entirely without jeopardy to your academic status, GPA or standing with the university. If you desire to withdraw, please close your internet browser and notify the principal investigator at this email: d.bacic@csuohio,edu. Or, if you prefer, inform the principal investigator as you leave.

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Questions about your Rights as Research Participants
I understand that if I have any questions about my rights as a research subject I can contact for CSU's Institutional Review Board at (216) 687-3630

I have read, understood, and desire of my own free will to participate in this study.

SIGNITURE DATE

APPENDIX A: Tasks – Study #2

In which month is there the greatest actual Net Income for three work centers combined?

Work Center	May Actual	May Plan	June Actual	June Plan	July Actual	July Plan	August Actual	August Plan	September Actual	September Plan	October Actual	October Plan
Work Center A	400.0	380.0	380.0	380.0	280.0	380.0	360.0	380.0	440.0	380.0	300.0	380.0
Work Center B	360.0	330.0	320.0	330.0	300.0	330.0	280.0	330.0	395.0	330.0	330.0	330.0
Work Center C	400.0	360.0	300.0	360.0	320.0	360.0	340.0	360.0	395.0	360.0	360.0	360.0

Net Income - Actual vs. Plan

Select correct month:
A) May B) June C) July D) August E) September F) October

Figure 16: Cell 1 - Simple-Spatial Task - Table

In which month is there actual unit rate the greatest for all three factories combined?

Select correct month:
A) May B) June C) July D) August E) September F) October

Figure 17: Cell 2 – Simple-Spatial Task - Graph

You are trying to understand actual monthly revenue information for a particular product in six firms relative to expenses

How much are Revenues above Expenses for Factory E in the month of July?

	May		June		Jul		August		September		October	
Firms	Revenues	Expenses	Revenues	Expenses	Revenues	Expenses	Revenues	Expenses	Revenues	Expenses	Revenues	Expenses
Firm A	400.0	380.0	380.0	380.0	360.0	380.0	440.0	380.0	280.0	380.0	300.0	380.0
Firm B	360.0	330.0	320.0	330.0	280.0	330.0	400.0	330.0	300.0	330.0	330.0	330.0
Firm C	420.0	360.0	300.0	360.0	340.0	360.0	400.0	360.0	320.0	360.0	360.0	360.0
Firm D	418.0	420.0	440.0	418.0	484.0	418.0	418.0	418.0	396.0	418.0	308.0	418.0
Firm E	363.0	360.0	396.0	360.0	440.0	360.0	352.0	360.0	308.0	360.0	330.0	360.0
Firm F	396.0	396.0	462.0	396.0	440.0	396.0	330.0	396.0	374.0	396.0	352.0	396.0

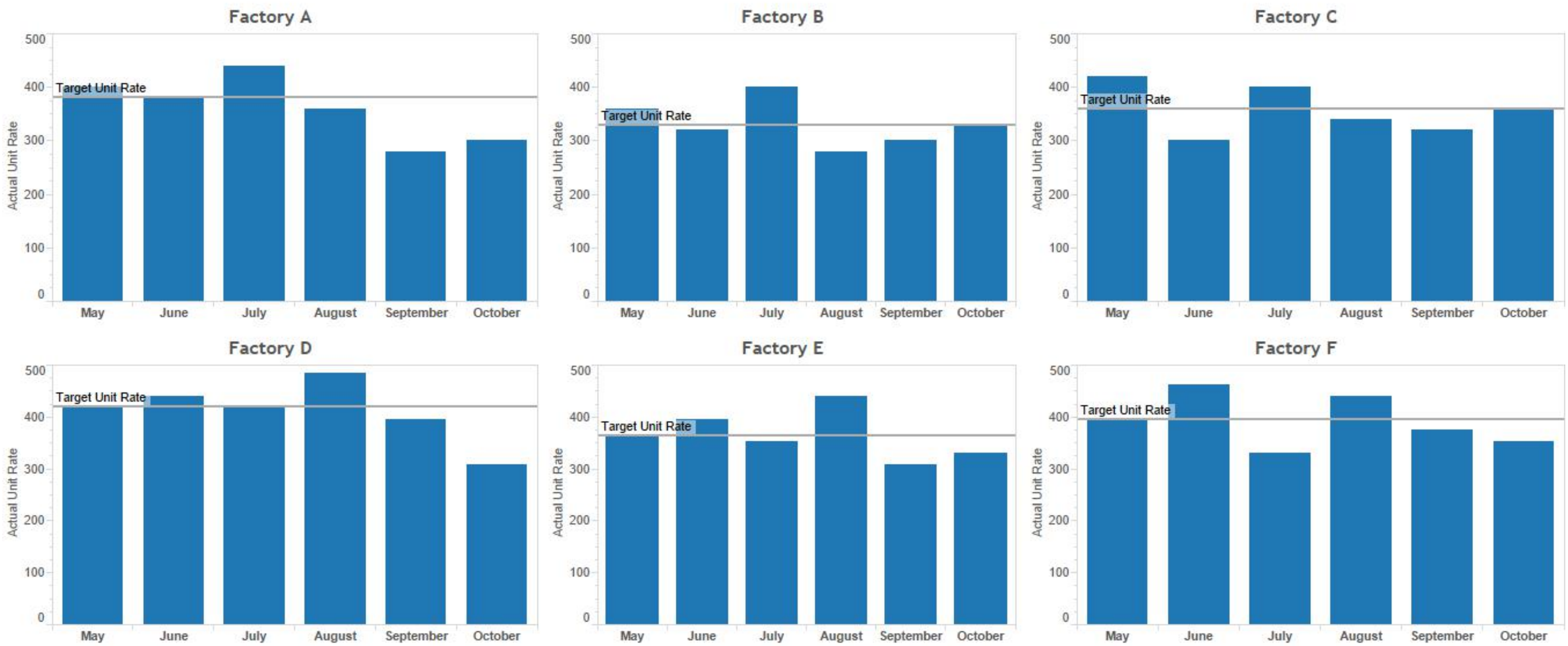
Select correct answer
A) 70 B) 65 C) 85 D) 80 E) None

Figure 18: Cell 3 - Simple Symbolic Task - Table

You are trying to understand actual monthly Activity Based Costing information for a particular activity in three factories relative to a target unit rate.

How much is the actual unit rate above target for Factory B in the month of July?

..



Select correct answer
A) 60 B) 75 C) 70 D) -10 E) None

Figure 19: Cell 4 - Simple-Symbolic Task - Graph

Using information presented below you are to assess which firm(s) meet **all** conditions in **both** financial analysis scenarios

Scenario 1:
- Sales have been increasing every year between 2000 and 2011
- Gross Profit % > 25% or Profit Margin >5%
- Return on Assets (ROA) >6.25% and Return on Equity (ROE) > 50%

Scenario 2:
- In 2000 - 2011 time period, EPS has been consistently in top three out of 6 firms
- Current Ratio >100%
- Debt-to-Equity ratio is less than 590% and Debt-to-Assets is less or equal to 90%

Ratio Analysis

Firm	ROA	ROE	Current Ratio	Debt-to -Equity	Gross Profit %	Profit Margin %	Debt-to-Assets
Firm 1	16.67%	53.85%	150.00%	223.08%	30.93%	12.96%	69.05%
Firm 2	18.54%	126.67%	115.79%	583.33%	35.91%	17.27%	85.37%
Firm 3	9.38%	37.50%	120.00%	300.00%	22.00%	10.00%	75.00%
Firm 4	16.80%	84.00%	135.00%	400.00%	48.39%	13.55%	80.00%
Firm 5	10.00%	40.00%	111.11%	300.00%	27.78%	11.11%	75.00%
Firm 6	6.25%	25.00%	102.50%	300.00%	33.33%	9.52%	75.00%

EPS Trend Analysis

Firm	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Firm 1	2.340	2.500	2.050	2.860	2.700	2.650	2.700	2.500	2.454	2.545	3.500
Firm 2	3.070	2.950	3.340	3.170	3.060	3.340	3.240	3.380	3.140	3.340	3.800
Firm 3	1.560	1.500	1.740	1.640	1.500	1.840	1.500	1.740	1.640	1.500	1.500
Firm 4	2.850	2.950	2.650	3.390	3.260	3.150	3.440	3.140	2.954	3.385	4.200
Firm 5	1.007	0.967	1.067	1.020	1.040	1.000	1.160	1.093	1.000	1.227	1.333
Firm 6	1.040	1.000	1.160	1.093	1.000	1.227	1.000	1.160	1.093	1.000	0.667

Return Analysis

Firm	ROA	Target ROA	ROE	Target ROE
Firm 1	16.67%	6.25%	53.85%	50.00%
Firm 2	18.54%	6.25%	126.67%	50.00%
Firm 3	9.38%	6.25%	37.50%	50.00%
Firm 4	16.80%	6.25%	84.00%	50.00%
Firm 5	10.00%	6.25%	40.00%	50.00%
Firm 6	6.25%	6.25%	25.00%	50.00%

Sales Trend by Company

Firm	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Firm 1	225,000	278,000	240,000	275,000	265,000	280,000	295,000	300,000	275,000	285,000	270,000
Firm 2	110,000	128,000	143,500	150,000	157,000	169,000	179,000	183,400	189,000	195,000	220,000
Firm 3	143,000	150,000	165,000	154,400	165,000	156,000	150,000	165,000	154,400	165,000	150,000
Firm 4	192,000	222,000	238,500	259,000	272,000	280,000	285,000	292,000	300,000	305,000	310,000
Firm 5	103,000	114,000	134,500	120,000	143,000	150,000	165,000	154,400	165,000	156,000	180,000
Firm 6	91,000	93,000	96,000	96,750	97,500	98,200	99,000	99,500	99,750	101,000	105,000

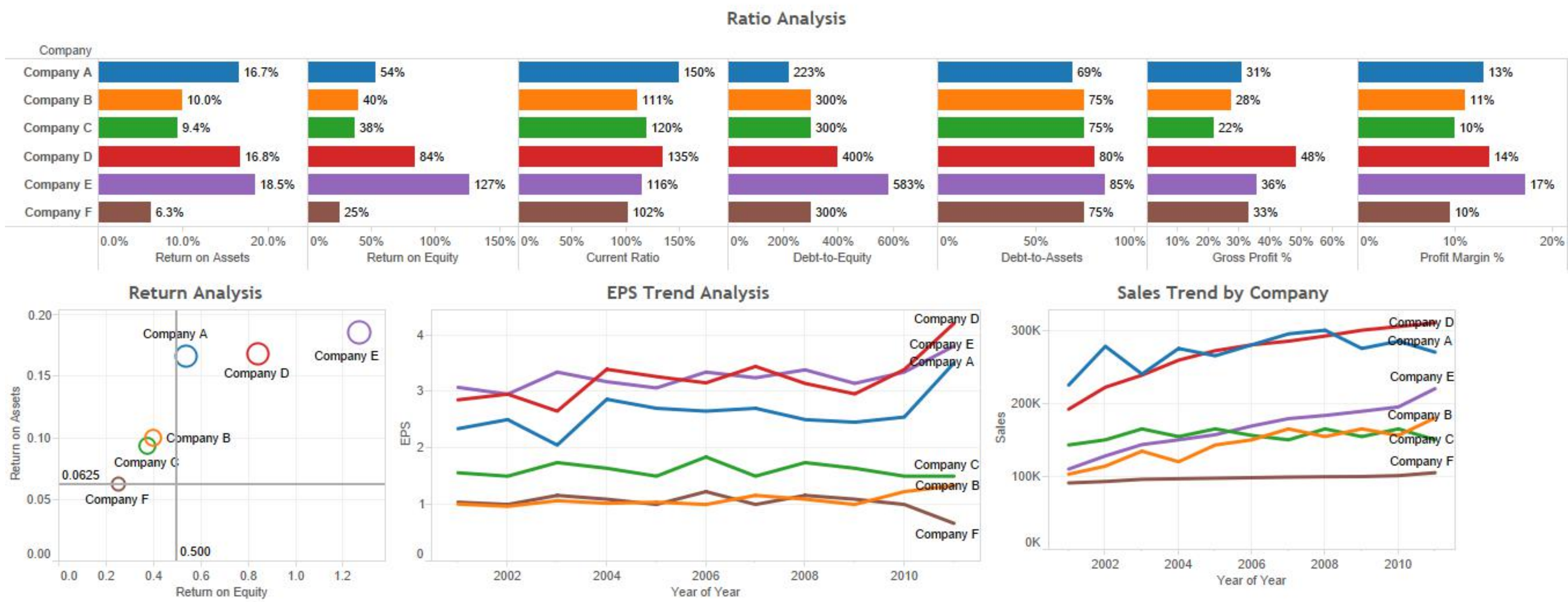
Select Answer(s):
A) Firm 1 B) Firm 2 C) Firm 3 D) Firm 4 E) Firm 5 F) Firm 6 G) None

Figure 20: Cell 5 - Complex-Spatial Task - Table

Using information presented below you are to assess which companies meet **all** conditions in **both** financial analysis scenarios

Scenario 1:
- Sales have been increasing every year between 2000 and 2011
- Gross Profit % > 25% or Profit Margin >5%
- Return on Assets (ROA) >6.25% and Return on Equity (ROE) > 50%

Scenario 2:
- In 2000 - 2011 time period, EPS has been consistently in top three out of 6 companies
- Current Ratio >100%
- Debt-to-Equity ratio is less than 500% and Debt-to-Assets is less or equal to 85%



Select Answer(s):
A) Company A B) Company B C) Company C D) Comapny D E) Company E F) Company F G) None

Figure 21: Cell 6 - Complex-Spatial Task - Graph

Procedure
Select locations that meet <u>all three</u> decision rules.
1) Total Costs are less than or equal to $78,000.
2) Transportation Costs are no more than 50% of Total Costs
3) Labor Costs are no more than 10% of Total Costs

Warehouse Location	Labor Costs	Marketing Costs	Transportation Costs	Taxes	Total Costs
Location 1	7,500	16,500	35,000	22,500	81,500
Location 2	6,000	14,500	45,000	13,000	78,500
Location 3	4,000	18,000	30,000	16,000	68,000
Location 4	5,000	15,000	33,000	17,000	70,000
Location 5	6,000	15,500	38,500	25,000	85,000
Location 6	7,500	16,000	33,000	17,000	73,500

Select Answer(s):
A) Location 1 B) Location 2 C) Location 3 D) Location 4 E) Location 5 F) Location 6

Figure 22: Cell 7 - Complex-Symbolic Task - Table

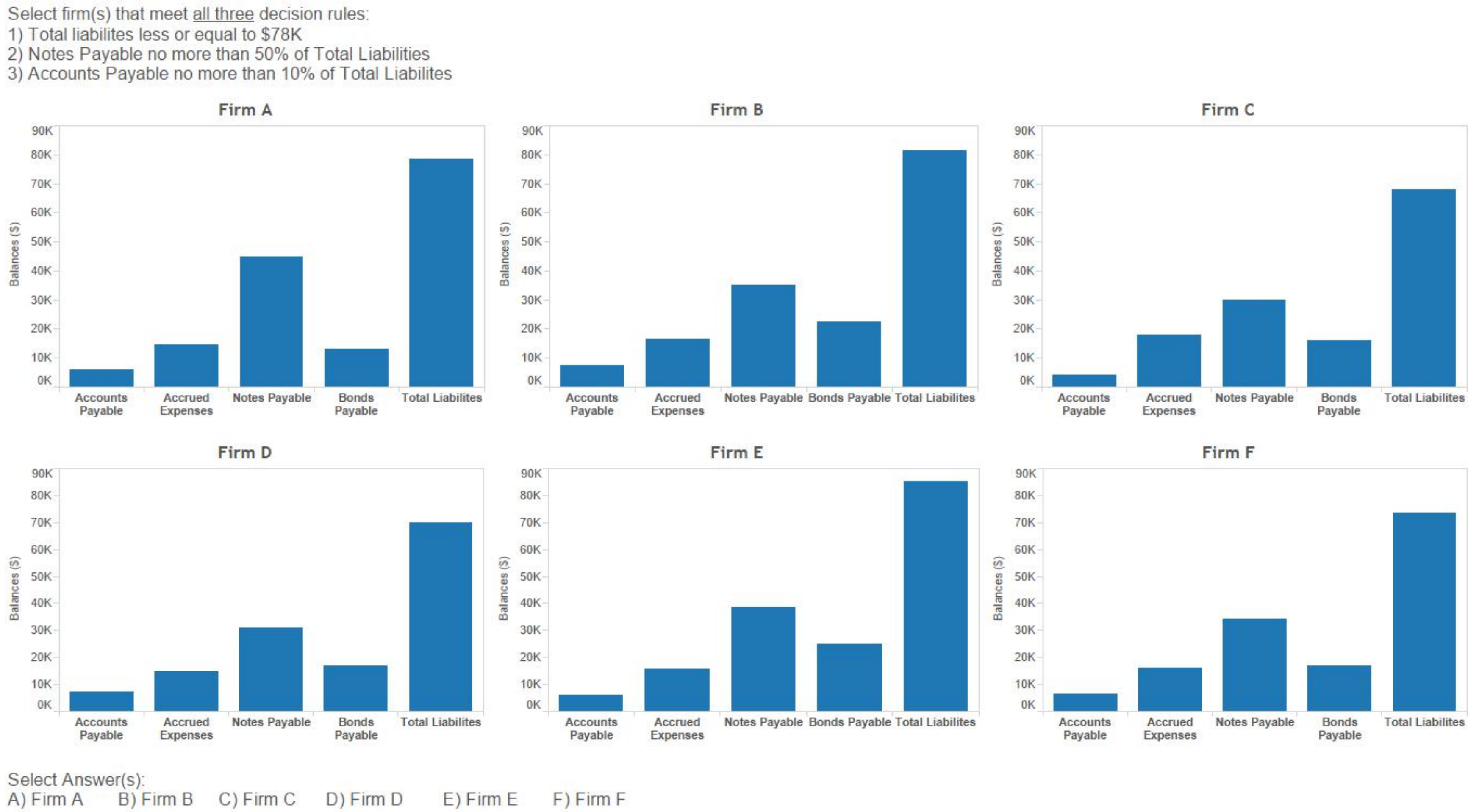


Figure 23: Cell 8 - Complex-Symbolic Task - Graph

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