Transactions on Human-Computer Interaction

Volume 10 | Issue 3

9-2018

Task-Representation Fit’s Impact on Cognitive Effort in the Context of Decision Timeliness and Accuracy: A Cognitive Fit Perspective

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DOI: 10.17705/1thci.00107

Available at: http://aisel.aisnet.org/thci/vol10/iss3/2

Task-Representation Fit's Impact on Cognitive Effort in the Context of Decision Timeliness and Accuracy: A Cognitive Fit Perspective

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Abstract:

Cognitive fit theory (CFT) has emerged as a dominant theoretical lens to explain decision performance when using data representations to solve decision making tasks. Despite the apparent consensus regarding cognitive effort's theoretical criticality in CFT-based research, researchers have made limited attempts to evaluate and empirically measure cognitive effort and its impact. Unlike prior CFT-based literature that has theorized only the role of cognitive effort, in our empirical study, we presented information and tasks to 68 participants and directly measured cognitive effort to understand how cognitive fit impacts it and how it impacts decision performance. We found that 1) cognitive fit had an impact on cognitive effort only for more complex tasks and 2) cognitive effort had an impact on decision performance time but not on decision performance accuracy. These findings enhance our understanding of an established IS theory and encourage more research on the cognitive underpinnings of CFT.

Keywords: Cognitive Effort, Cognitive Fit Theory, Visualization, Decision Making, Cognitive Fit.

Teresa Shaft was the accepting senior editor for this paper.

1 Introduction

In recent years, practitioners and academics have found renewed interest in the visual display of business information and its usefulness in decision making. Not surprisingly, technology vendors have responded through business intelligence (BI) systems that feature graphical data- and visual data-discovery capabilities, while self-service dashboards have become as popular as ever (DeBois, 2015; Gartner, 2016; Howson, 2010). However, the initial excitement over data visualization capabilities has decreased as researchers and practitioners have found it difficult to assess how these capabilities impact users' work and decision making (Bresciani & Eppler, 2015). Indeed, the challenges associated with efficiently and effectively displaying business information are as old as the information systems (IS) field itself. Today, these challenges have become even more prominent as users operate in environments that feature increased data complexity, volume, and velocity and in which decision making and data analysis tasks depend on visually intensive applications more than ever before (Simon, 2014).

Amid data visualization's increased prominence in BI and the resulting proliferation of popular presentation formats and display options, we take a closer look at business data visualization research's theoretical underpinnings and explanatory power. We focus on one of the dominant theoretical lenses, cognitive fit theory (CFT) (Vessey, 1991; Vessey & Galletta, 1991), a theory that initially emerged over 25 years ago as a way to explain individuals' decision performance (accuracy and speed) when they use graphical and tabular displays. The theory successfully explained a series of seemingly conflicting studies; consequently, the broader research community adopted it as a dominant lens to predict decision performance when leveraging competing data-presentation formats. Today, the CFT literature has matured: researchers have extended the original theory multiple times and used it as the theoretical foundation for a growing list of task types, presentation formats, and problem contexts. Yet, it fundamentally remains focused on task-representation fit as a predecessor to decision performance by suggesting that fit's impact on decision makers' cognitive effort (CE) constitutes the underlying mechanism that influences decision timeliness and accuracy. While cognitive effort lies at the heart of CFT, few researchers have explicitly incorporated this construct in research models or empirically measured this primary cognitive mechanism (Bačić & Fadlalla, 2016). We believe that we may better understand this important theoretical lens and its impact by emphasizing and measuring its underlying cognitive elements. Therefore, in this research, we do not introduce a brand-new construct but rather investigate the mechanism that research has already theorized and that has a central role in cognitive fit; however, researchers have not yet measured or empirically tested it in this context. We empirically evaluate the role of cognitive effort and reinvestigate some basic assumptions behind CFT in the context of varied task type and complexity.

To address these gaps, in this research, we succinctly review the CFT literature by documenting the IS literature's prevalent view that the fit between task and external representation impacts decision/problem solving performance through its impact on users' cognitive effort. Further, we provide initial empirical evidence about how we can advance this mature theoretical model. Lastly, we suggest that directly measuring cognitive effort represents an opportunity to enhance and clarify the explanatory power of CFT

We hope that this research influences CFT-based research to focus more on understanding the role that CE—as the main mechanism through which cognitive fit affects task performance—could play in CFT. We suggest that, by focusing on understanding cognitive effort, the research community may discover new insights into what drives efficacious and efficient presentation formats—even potentially beyond cognitive effort. We hope that this research provides a few steps toward applying CFT in a more nuanced way.

2 Literature

2.1 Cognitive Fit Theory

Vessey (1991) and Vessey and Galletta (1991) developed CFT to explain the inconsistencies that early research on tables versus graphs found by attributing performance differences to how well the presentation format matches the task at hand (Baker, Jones, & Burkman, 2009). Namely, the theory suggests that, if both the problem representation and problem solving task involve the same information type, a "cognitive fit" exists between them. When the information that the presentation emphasizes matches the task, decision makers can use the same mental representation and decision processes for both the presentation and the task, which results in faster and more accurate solutions (Vessey, 1991). Researchers have since expanded the original theory various times to further explain problem solving performance by explicitly including problem solving skills (Vessey & Galletta, 1991), evaluating the congruence between the external information and the internal representation (Chandra & Krovi, 1999), and differentiating between the two types of representations of the problem domain (i.e., internal and external representation) (Shaft & Vessey, 2006). However, CFT and its extensions share the underlying assumption that problem solving processes that human problem solvers use in completing the task help to reduce processing effort (Vessey & Galletta, 1991).

After CFT appeared, the theory gained rapid adoption in the IS academic literature. Over more than a quarter century (1991-2018) and through over 50 research papers, several common themes have emerged. First, the available research has primarily focused on exploring the implications of problem solving task characteristics and, to some degree, individual characteristics (Cardinaels, 2008; Dunn & Grabski, 2001; Hubona, Everett, Marsh, & Wauchope, 1998; Khatri, Vessey, Ramesh, Clay, & Park, 2006; Shaft & Vessey, 2006). Over time, researchers expanded the initial theory's focus on tasks characteristics and, in particular, spatial versus symbolic tasks (Vessey, 1991; Vessey & Galletta, 1991), to other types of tasks (Dennis & Carte, 1998; Hong, Thong, & Kar Yan, 2004; Khatri, Vessey, Ram, & Ramesh, 2006; Sinha & Vessey, 1992). Second, while more studies have considered tables and graphs than any other representation format, the variety in such formats has nevertheless expanded. Some of the new problem representations that researchers have considered include modeling tool types (Agarwal, Sinha, & Tanniru, 1996; Khatri et al., 2006), maps versus route directions (Dennis & Carte, 1998; Hubona et al., 1998), online interface design formats (Adipat, Zhang, & Zhou, 2011; Kamis, Koufaris, & Stern, 2008), and many others. Third, while a significant number of CFT-based studies have found support for their hypotheses, the literature still contains unsupported and even contradictory findings (Dennis & Carte, 1998; Frownfelter-Lohrke, 1998; Speier, 2006).

Last, and the most salient theme for this research, in reviewing the literature, we found that studies have largely theorized processing effort as the mechanism behind the impact that data presentation has on decision performance even though they refer to it under different names such as cognitive effort, cognitive load, burden, and workload (Bačić & Fadlalla, 2016). According to CFT, if an external problem representation does not match to the task, little exists to guide the decision maker in solving a task, and they must exert greater cognitive effort to transform the information into a form suitable for solving that particular type of problem (Vessey, 1994). CFT-based researchers have adopted this view because they have specifically identified the condition of fit between data representation and task as impacting cognitive effort. We provide direct quotes from various influential CFT-based studies in Table 1 as the evidence of this adopted view.

Similarly, the same research stream has embraced the connection between cognitive effort and decision performance. More specifically, empirical research directly states that effort negatively impacts decision performance (see Table 2).

Despite the apparent consensus regarding cognitive effort's criticality, little research has measured the impact that data representation has on cognitive effort or assessed the impact that users' cognitive effort has on decision making efficiency and effectiveness. Only a handful of studies have approached the issue by including the somewhat related perceived ease of use (Adipat et al., 2011; Dunn & Grabski, 2001; Khatri et al., 2006). However, most of these studies have not found support for their hypothesized relationships between cognitive fit and ease of use, between cognitive load and ease of use (Li, Santhanam, & Carswell, 2009), or between workload and ease of use (Shen, Carswell, Santhanam, & Bailey, 2012). Extant research in the online shopping context has used decision cognitive effort but found that cognitive fit had no impact on it (Hong et al., 2004). Another study (Huang, Tan, Ke, & Wei, 2013) focused on comprehension effort found significant results based on CFT; however, the scale items the study used reveal closeness to perceived ease of use and task complexity (i.e., distinct constructs from the cognitive effort in CFT).

By directly measuring cognitive effort, we address an important and essential missing element in the current CFT-based literature (Bačić & Fadlalla, 2016) and take up previous calls to identify relevant factors in problem solving so that experimental research can control or else directly measure them (Agarwal et al., 1996). Therefore, in Section 2.2, we evaluate critical findings from the cognitive psychology and decision making literatures as they relate to cognitive effort and its measurement.

Table 1. Fit and Cognitive Effort: Literature Quotes*

Paper	Quote
Vessey & Galletta (1991)	"One of the ways to reduce **processing effort** is to facilitate the problem-solving processes that human problem solvers use in completing the task. This can be achieved by matching the problem representation to the task, an approach that is known as cognitive fit" (p. 65). "Supporting the task to be accomplished with the display format leads to minimization of both **effort and error**" (p. 81).
Dennis & Carte (1998)	"Choosing decision processes that match the information presentation minimizes **effort,** because using a different process requires the decision maker to expend more **effort** to transform the information before using it" (p. 197). "**Effort** is minimized when analytical processes are used for symbolic information, so decision makers presented with information in symbolic form are more likely to choose analytical processes" (p. 197). "Few took the **effort** (i.e., cost) to translate the spatial data into the precise underlying numeric data it represented" (p. 200). "We believe that the higher cost of accurately processing the detailed numeric data induced decision makers to not expend the needed **effort**" (p. 201).
Hubona et al. (1998)	"This paradigm of cognitive fit has a characteristic such that consistent mental representations reduce the **mental effort** required to solve a problem" (p.708).
Chandra & Krovi (1999)	"Message passing is assumed to be a natural metaphor for reducing **cognitive strain** to help reduce a broad search that is typical in a PN mode" (p. 277). "The larger the network, the more the traversal that will be required. This should impose **cognitive load**, thereby, increasing the probability of errors" (p. 278). "This paper suggests that representational congruence is one way to reduce such a **cognitive load**. Similar in principle to the construct of cognitive fit" (p. 272).
Mennecke, Crossland, & Killingsworth (2000)	"Since an Image contains an integrated view of the relevant data, this should create a decision-making environment that more consistently fits the cognitive requirements of the decision maker and thereby reduces **cognitive load**" (p. 607).
Goswami, Chan, & Kim (2008)	"We believe that the higher cost of accurately processing the detailed numeric data induced decision makers to not expend the needed **effort**" (p. 336).
Baker et al. (2009)	"Visual representations that require a high level of **cognitive effort** from viewers in order to interpret the representation are less desirable than visual representations that require relatively less effort" (p. 539). "When a common facial expression is not recognized, a greater amount of **cognitive effort** is required to apprehend the meaning of the face (Umanath and Vessey, 1994)" (p. 545).
Adipat et al. (2011)	"If a mismatch between task and information presentation occurs, users must make extra **cognitive effort** to transform information into a format that is suitable for accomplishing the task." "Both hierarchical text summarization and colored keyword highlighting adaptations are aimed at enhancing information scent in the tree-view hierarchy to alleviate users' **cognitive load and efforts**, especially when browsing complex Web pages" (p. 103).
Chan, Goswami, & Kim (2012)	"...problem representation will determine the extent of **cognitive effort** required by users to mentally process the information to process the task" (p. 26). "In order to perform the task using the A1 and R1C1 problem representations, users have to expand significant **cognitive effort** as the task is a visual spatial task while the problem representations are not" (p. 33-34).
Dilla, Janvrin, & Jeffrey (2013)	"Since nonprofessional investors tend to have lower levels of task-specific knowledge and experience, they will rely on these graphical displays to reduce **cognitive effort** when making earnings evaluations and investment judgments, regardless of task type. On the other hand, professional investors will not rely on graphical displays of pro forma information when engaged in the relatively simple task of evaluating current year earnings performance. They will rely on these graphical displays to **reduce cognitive effort** only when performing the more complex tasks of making future earnings potential and investment amount judgments" (pp. 38-39).
Giboney, Brown, Lowry, & Nunamaker (2015)	"…and cognitive fit reduces **cognitive effort**…" (p. 8).

* All papers except Baker et al. (2009) are empirical. Vessey and Galletta (1991) and Chandra and Krovi (1999) provide strong theoretical contributions to CFT (supported with data).

Table 2. Cognitive Effort and Performance: Literature Quotes

Paper	Quote
Umanath & Vessey (1994)	"This process may result in lower prediction accuracy due to increased **cognitive effort** required…" (p. 809).
Agarwal et al. (1996)	"A second, related explanation for the lack of significant results for object-oriented tasks and structure subtasks is that structure is inherently easier to model. If that is the case, the **cognitive burden** involved in solving structure-oriented tasks would be small; hence, the effects of a match between the tool and the task would not be discernible as improvement in performance" (p. 154).
Chandra & Krovi (1999)	"The larger the network, the more the traversal that will be required. This should impose **cognitive load**, thereby, increasing the probability of errors" (p. 278).
Mennecke et al. (2000)	"….this would be typical of a Figuration and would require greater **cognitive effort** and consume more time" (p. 607).
Dunn & Grabski (2001)	"Cognitive fit predicts that users of information that is consistent across problem and task representation will perform more quickly than users of inconsistent information, because of increased **cognitive costs** to process information" (p. 63).
Adipat et al. (2011)	"If a mismatch between task and information presentation occurs, users must make extra **cognitive effort** to transform information into a format that is suitable for accomplishing the task. This extra **effort** can result in inferior task performance (Vessey 1994)" (p. 103).
Chan, Goswami, & Kim (2012)	"Since mental transformation takes time and **effort**, it affects task performance (Vessey, 2006)" (p. 37).

2.2 Cognitive Effort

Researchers have defined cognitive effort as the total amount of cognitive resources (e.g., perception, memory, and judgment) that an individual needs to complete a task (Cooper-Martin, 1994; Russo & Dosher, 1983). Cognitive effort research originated as a theoretical construct in cognitive psychology (Johnson & Payne, 1985; Kahneman, 1973; Navon & Gopher, 1979; Norman & Bobrow, 1975; Thomas, 1983), which widely recognized it to impact human performance. In addition to extensive research on cognitive effort in cognitive psychology, the literature that focuses on the role that cognitive effort has in decision making has particular relevance to this study; in particular, it suggests that decision makers primarily focus on minimizing cognitive effort (Bettman, Johnson, & Payne, 1990; Cooper-Martin, 1994; Johnson & Payne, 1985).

Researchers have measured cognitive effort via several methods and lenses. One of the earliest methods, called "the cost of thinking" (Shugan, 1980), involves comparing alternatives across an attribute. Similarly, Bettman et al. (1990) used elementary information processes (Johnson & Payne, 1985), a system that describes a heuristic as a sequence of mental events, to predict cognitive effort as it relates to response time and for subjective reports. Further, research suggests that one can evaluate cognitive effort through the dimension of time, cognitive strain, and a concept labeled "total cognitive effort" (Cooper-Martin, 1994). Researchers have defined the time dimension as the period (duration) over which an individual expands the cognitive effort and examined it via self-reports (Bettman et al., 1990; Wright, 1975) or as objective decision time (Christensen-Szalanski, 1980). Research has measured the second dimension, cognitive strain, as a self-reported subjective measure (Cooper-Martin, 1994; Wright, 1975). Lastly, research has used total cognitive effort, which measures the number of comparisons that a user makes in a statement about a choice (Cooper-Martin, 1994). This concept captures the cost element to the effort; namely, 1) number of attributes processed (Wright, 1975), 2) number of alternatives processed (Wright, 1975), and 3) number of comparisons processed (Shugan, 1980).

In our context, cognitive strain represents the most appropriate measure of cognitive effort since the perception of time does not capture effort intensity and research has found it to lack discriminant validity when used with cognitive strain (Cooper-Martin, 1994). Additionally, CFT models typically incorporate performance time as a dependent variable. Similarly, our research captures the number of attributes and statements processed through task complexity, making the use of "total cognitive effort" lens inappropriate in our context.

3 Model and Hypotheses

Based on CFT and CFT-based literature, we suggest the need to more directly recognize the role of cognitive effort as Figure 1 represents.

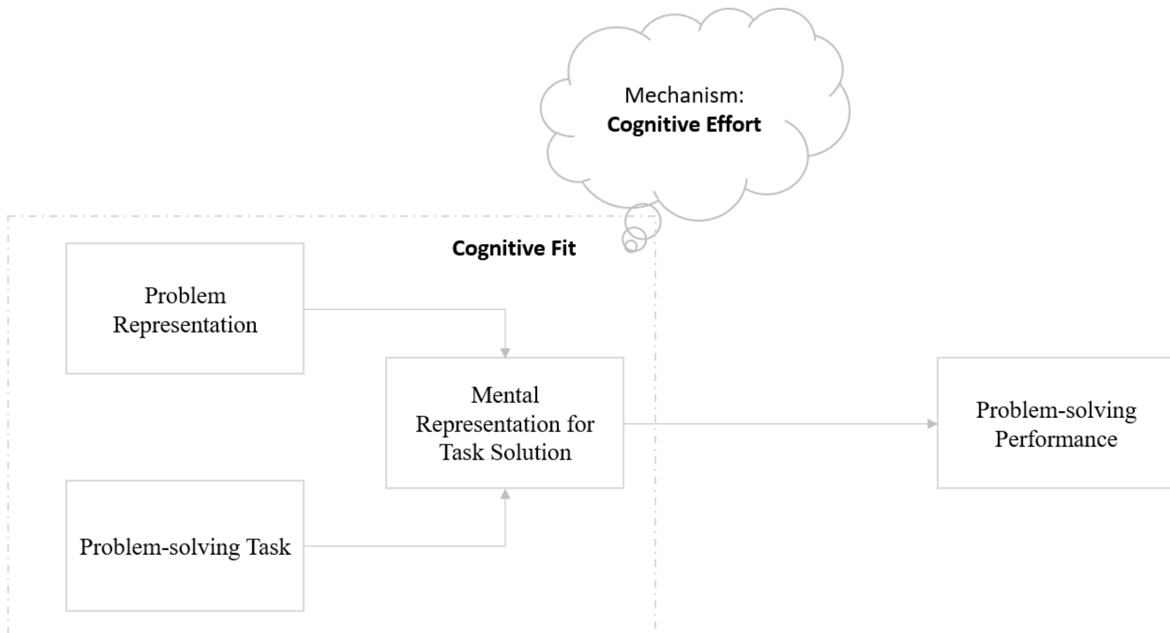

Figure 1. Research Model (based on Vessey, 1991; Vessey & Galletta, 1991)

As we highlight in our literature review (see Table 1), CFT suggests that cognitive fit will lead to lower cognitive effort when compared to an alternative scenario without such a cognitive fit. However, before stating this relationship as a hypothesis, CFT-based research suggests the need to examine the impact of cognitive fit on cognitive effort in the contexts of tasks that vary in information type/task requirements and complexity.

First, to solve the difficulty in developing a link between presentation format and task characteristics due to the large number of characteristics and the many ways in which one can describe them, Vessey (1991) proposed a two-category classification based on information type 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 one to make associations or perceive relationships in the data, such as understanding a firm's performance by considering monthly sales trend by product segments along with its profitability strengths and weaknesses relative to its peers in those segments. Symbolic tasks, on the other hand, involve extracting discrete and precise data values (Vessey & Galletta, 1991), such as looking up an individual's tax bracket. Given 1) CFT's original context, 2) the link between spatial/symbolic tasks and tables/graphs as data-representation methods, and 3) the significance of tables and graphs in business information visualization context, we adopt these two problem-solving cognitive task types as a task nature component of cognitive fit in this research.

Second, CFT originally focused on addressing decision performance under elementary/simple mental tasks (Speier, 2006). However, given the reality of today's decision making and its complexity (Abbasi, Sarker, & Chiang, 2016), researchers quickly recognized the potential to apply CFT to complex tasks (Vessey & Galletta, 1991; Dennis & Carte, 1998). Consequently, a stream of CFT-based research focused on exploring fit's impact on task complexity in contexts such as financial statement analysis (Frownfelter-Lohrke, 1998), geographic information systems (Dennis & Carte, 1998), interruptions (Speier, Vessey, & Valacich, 2003), operation management (Speier, 2006), and quality assurance (Teets, Tegarden, & Russell, 2010). Note that research focused on task-representation fit in more complex tasks has predominantly found partial (Speier, 2006; Teets et al., 2010) to contradictory (Frownfelter-Lohrke, 1998) support for cognitive fit's decision performance implications. The mixed nature of these results further emphasizes the need to understand the role of cognitive effort across tasks of varying complexities.

In summary, the existing CFT research suggests that cognitive effort represents an important mechanism that links data representation with performance and emphasizes the appropriateness of approaching tasks from both a complexity (simple vs. complex) and representation lens (spatial vs. symbolic). Consequently, task classification that involves the combination of four tasks (i.e., simple symbolic, simple spatial, complex symbolic, and complex spatial) (Speier, 2006) pertains most to our study.

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.

CFT assumes that problem solving processes that human problem solvers use in completing tasks facilitate processing effort (Vessey & Galletta, 1991). According to CFT, when a mismatch between task, representation, and decision processes occurs, one of two processes will occur. Decision makers may transform the presented data to better match the task, which can increase task-completion time and decrease task accuracy because any transformation can introduce errors (Vessey, 1991). Alternatively, especially when decision makers cannot alter the presented data, they may adjust their decision processes to match the presentation, which can increase cognitive effort. While existing empirical research widely supports the notion that an increase in cognitive effort results in an increase in task-completion time (Vessey & Galletta, 1991), CFT-based research findings that explore the relationship between cognitive fit (and resulting cognitive effort mechanism) and decision accuracy offers less conclusive findings. Potentially competing forces influence the impact that effort has on decision accuracy. On one hand, CFT suggests that the mismatch between the task and presentation format, could influence a decision maker to have to expend more effort, which research has hypothesized to result in lower ability to accurately solve the task (see quotes in Table 2). On the other hand, cost-benefit principles (Beach & Mitchell 1978; Einhorn & Hogarth 1981; Johnson & Payne 1985; Klein & Yadev 1989) suggest that, when deciding, we seek to minimize effort. Per cost-benefit principles, decision makers will forgo some task accuracy in order to expend less effort. Therefore, a decision maker's readiness to exert more cognitive effort in dealing with a difficult task would lead to a higher decision accuracy, which contradicts the CFT-based link between effort and accuracy.

Although we adopt CFT's implied direction of the relationship between cognitive effort and decision performance in our context, we formally state the relationship between cognitive effort on decision time in more certain terms (one *leads* to another), while, in the case of the relationship between cognitive effort and accuracy, we recognize the relationship complexity and describe that relationship with less implied causality (one is *associated* with another). Consistent with the existing CFT-based research and aligned with H1 through H4, we state each hypothesis for both simple and complex tasks. We do not, however, separate hypotheses for task type (spatial and symbolic) as task type represents an element of cognitive fit and not a distinct category that determines how cognitive effort impacts performance.

H5: For simple tasks, an increase in cognitive effort increases the amount of time that a decision maker needs to make a decision.

H6: For simple tasks, an increase in cognitive effort is associated with a decrease in decision accuracy.

H7: For complex tasks, an increase in cognitive effort increases the amount of time that a decision maker needs to make a decision.

H8: For complex tasks, an increase in cognitive effort is associated with a decrease in decision accuracy.

4 Methodology

To empirically test our hypotheses, we conducted an experiment with 68 (usable) human participants who each completed four of eight tasks. Tasks ranged from simple to complex and spatial to symbolic.

Participants solved those tasks using tabular and/or graphical presentation formats. In our experiment, we also measured participants' perceptions about their own cognitive effort and actual performance (time and accuracy) for each task. In Section 4.1, we describe the experimental design and procedures in greater detail.

4.1 Research Design

The research design had two parts. In the first part (which tested H1 through H4), we used a three-factor experimental design. To allow for analysis flexibility, we used task complexity (simple, complex) and task type (spatial, symbolic) to create four tasks (simple spatial, simple symbolic, complex spatial, and complex symbolic) with data representation type (table, graph). As a result, we created an eight-cell two by two by two factorial design. We employed a completely counterbalanced, fully factorial design in which we randomly assigned users to one of eight scenarios. This design provided eight combinations of representations (tabular, graphical) and tasks (simple spatial, simple symbolic, complex spatial, and complex symbolic). In each scenario, users completed all four tasks. We counterbalanced the task-representation combination order in each scenario. We used cognitive effort as the dependent variable for this first portion of the study. In the second portion of the study, we regressed cognitive effort against two dependent variables, time (H5 and H7) and accuracy (H6 and H8), to test the remaining hypotheses.

4.1.1 Tasks

We divided the task experimental conditions into simple and complex tasks with either symbolic or spatial cognitive requirements. We adopted Wood's (1986) view of task complexity, which defines the concept as 1) a function of the number of distinct information cues that one must process, 2) the number of distinct processes that one must execute, and 3) the relationship between the cues and processes. To separate tasks into simple versus complex, we created two tasks that required a low number of variables/information cues and calculations (simple) and two tasks that required a high number of variables/information cues and calculations (complex).

We developed the simple spatial, simple symbolic, and complex spatial tasks based on the existing CFT literature (Speier, 2006; Speier et al., 2003), and we adapted those tasks to the financial accounting domain. We created the complex spatial task specifically for this study. In the simple spatial task, we asked the participants to identify the month in which the actual unit rate was the highest for all three firms (adapted from Speier, 2006; Speier et al., 2003). This task required the participants to assess the relationship between data point (spatial) while trying to identify the month in which the unit rate was the highest for the combined locations. Following Wood's (1986) methodology to assess tasks, this simple spatial task required participants to use three information cues (unit rate, location, and month), add unit rates for each month and location, and then compare those unit rates across six months to find the optimal answer.

The simple symbolic task (adapted from Speier, 2006; Speier et al., 2003) required participants to obtain specific data by directly extracting information regarding unit rates for a specific location and a specific month (symbolic). Once they did so, they had to subtract target unit rate from actual unit rate to retrieve the correct answer. Following Wood's (1986) methodology to assess tasks, this simple symbolic task involved four information cues (actual rate, target rate, month, and location), one behavior (calculate), and subtraction between selected actual and target rate..

In the complex spatial task, the participants had to use existing information for six firms to assess which ones met two financial scenarios that each had three and/or conditions. Following Wood's (1986) methodology to assess tasks, this complex spatial task required participants to assess 17 information cues and use them in nine different acts of comparison. Further, the task required participants to assess the relationship between data points and did not require precision, which made it a spatial task as well.

The complex symbolic task comprised a firm-investment task based on a previously published operations management task (Speier, 2006; Speier et al., 2003) that we adapted to the financial accounting context. In the firm-investment task, we provided the participants with five different balance sheet (liabilities) line items/categories associated with six firms. They had to determine which firms to invest in. The complex symbolic task required participants to assess 11 information cues (dollar amount, firm, accounts payable, accrued expenses, notes payable, bonds payable, total liabilities, fixed amount of total liabilities, fixed percent limit for notes payable, and fixed percent limit for accounts payable) and perform acts of comparison and ordering. Given the number of the cues and behavioral acts, this task involved substantially more complexity for the user when compared to two simple tasks. Further, the task required participants to obtain specific data by directly extracting information, which made it a symbolic task.

4.1.2 Representation

Participants completed each experiment task with information represented via graph(s) or table(s). Each representation focused on supplying sufficient information to participants to correctly respond to each task. Researchers have criticized previous research for poor-quality representations and unequal levels of data in those two formats (Few, 2013). Thus, we focused on ensuring that both representation formats used best practices for visualizing information. Similarly, we ensured that each representation format displayed equivalently granular data. Lastly, to better control the cognitive processes that the participants needed to acquire and interpret the information, we ensured that each representation (and task problem statements) fit on one computer screen. As such, participants did not need to scroll or page down to see additional data. Appendix A shows an example of a complex spatial task and both representation formats[1].

4.1.3 Cognitive Effort

We measured cognitive effort (CE) using Cooper-Martin's (1994) cognitive strain scale (see Table 3). We removed two items from the original scale. We did not include perception of time since we used time as a dependent variable in our model. Similarly, we did not include an item that reflected the number of statements and alternatives because, in the context of this study, they formed part of task complexity.

Table 3. Cognitive Effort Scale Items

Items	Scale
1. I was careful about which answer I chose	Strongly disagree (1) to strongly agree (7)
2. I thought very hard about which answer to pick	Strongly disagree (1) to strongly agree (7)
3. I concentrated a lot while making this choice	Very little effort (1) to great deal of effort (7)
4. It was difficult for me to make this choice	Strongly disagree (1) to strongly agree (7)
5. I didn't pay much attention while making a choice	Strongly disagree (1) to strongly agree (7)
6. How much effort did you put into making this decision?	Very little effort (1) to great deal of effort (7)
* Adopted cognitive strain scale item from Cooper-Martin (1994).	

To ensure applicability to our context, we pretested the scale for reliability and inter-item correlations[2]. The Chronbach's alpha for the six items was 0.836, which exceeded the suggested value for reliability (> 0.7) (Nunnally, 1978), and the items displayed adequate internal consistency due to an average inter-item correlation of 0.459. The Cronbach's alpha concurs with the 0.82 Chronbach's alpha that Cooper-Martin (1994) reported. Both the high internal consistency and inter-item correlation confirm the appropriateness of the scale.

4.1.4 Decision Performance

Consistent with prior research, we measured decision performance via decision accuracy and decision time (Vessey, 1991; Vessey & Galletta, 1991). The experimental tool captured start and end times, which meant we could calculate total time. Based on pretest times, we expected that participants would need only up to one hour to complete the experiment; however, we placed no limit on the time they had to do so. In line with existing decision performance CFT-based literature, participants performed all intellective tasks (McGrath, 1984), which have optimal answers. To provide a standardized comparison across tasks, decision accuracy for each task was calculated as the percentage of the optimal solution achieved ((optimal solution-subject solution)/optimal solution)).

[1] We can provide all materials for all conditions upon request.
[2] The profile of the pretest group (n = 61) was consistent with the main study: in the pretest, 86% (54) were in 19-29 age group (89% (57) in the main study), 98% (60) were undergraduate students (99% (67) in the main study), and 51% (31) females (43% (29) in the main study).

4.2 Research Procedures

We recruited both undergraduate and graduate participants from various business classes at a large, public, university in the Midwestern United States. Students received partial course credit for their participation and could win one of three US$50 rewards for performance in terms of accuracy per unit of time. Two representation formats and four tasks resulted in eight conditions. Each participant performed one simple symbolic, one simple spatial, one complex symbolic, and one complex spatial task in random order. Although they had no time limit with which to perform the tasks, all participants completed the tasks and responses within one hour.

In total, 74 individuals volunteered to participate in this study. We could not use data for six participants, so we conducted our subsequent analyses with data from the remaining 68 (43% male and 57% female) who each participated in four out of eight experimental cells such that that each cell had N = 34. The participants' median age was 21 and average age was 23.5 (SD = 7.22), and all but one participant was an undergraduate student. Further, 25 percent participants had at least some work experience in professional or technical jobs, while 17.6 percent had some work experience as a manager or proprietor. On average, the participants had 0.83 years of experience (SD = 2.064) in a professional or technical role and 0.35 years of experience (SD = 0.91) as a manager or proprietor. Participants came from a wide number of business majors. Table 4 provides additional descriptive details about them.

Table 4. Participant Demographics

Variable	Count	
Gender	Male: 29 Female: 39	
Student type	Undergraduate: 67 Graduate: 1	
Major	Accounting: 14 Computer information systems: 4 Management & OSCM: 12 Marketing: 17 General business & other: 21	
Age	18-29: 61 30-39: 3 40+: 4	
Experience (Years)	**Professional**	**Managerial**
0	51	56
1-5	14	12
5-10	2	0
10+	1	0

The Cronbach's alpha for the self-reported CE six-item scale was .779, which exceeds the 0.7 acceptable threshold (Nunnally, 1978). Therefore, we used the average score of all six-items to measure participants' self-reported perception of CE. Furthermore, we used the Shapiro-Wilk test for normality, which suggested that the average score for CE was normally distributed.

We completed a manipulation check for task complexity by asking participants their perceptions of complexity on a seven-item Likert scale. We found that the difference in mean values for complex (M = 5.75, SD = 2.53) and simple (M = 3.49, SD = 2.25) tasks was significant ($F(68) = 95.675$, $p < 0.01$) and in the expected direction.

5 Results and Data Analysis

A two (task complexity: simple vs. complex) by two (task type: spatial vs. symbolic) by two (format: graph vs. table) between-subject ANOVA (Table 5) revealed an adjusted R squared of 12.6 percent and a significant main effect of task complexity ($F(1,264) = 31.911$; $p < 0.001$; MSE = 24.320; $\eta_p^2 = 0.108$). However, we found no significant effect 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 H1 to H4, we looked for a statistically significant interaction effect between task type and format on CE. The analysis of variance showed a significant interaction effect between task type and format on CE ($F(1,264) = 5.557$; $p = 0.019$; $MSE = 4.250$; $\eta_p^2 = 0.021$). We found no other interaction combination to be significant.

Table 5. ANOVA Results

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).						

Since we detected a significant interaction effect, we conducted pairwise t-tests to evaluate whether differences in CE means between cells that we hypothesize in H1 to H4 were significant. Table 6 summarizes the means and N for each experimental cell.

Table 6. Pairwise Comparison*

	Tasks			
Format	Simple		Complex	
	Spatial	Symbolic	Spatial	Symbolic
Tabular	Cell 1 4.554 (n = 34)	**Cell 4** **4.436** (n = 34)	Cell 6 5.554 (n = 34)	**Cell 7** **4.838** (n = 34)
Graphical	**Cell 2** **4.637** (n = 34)	Cell 3 4.775 (n = 34)	**Cell 5** **5.186** (n = 34)	Cell 8 5.216 (n = 34)
* CE (n) by experimental cell: bolded cells represent theorized state of cognitive fit.				

Figure 2 visually displays the same pairwise tests.

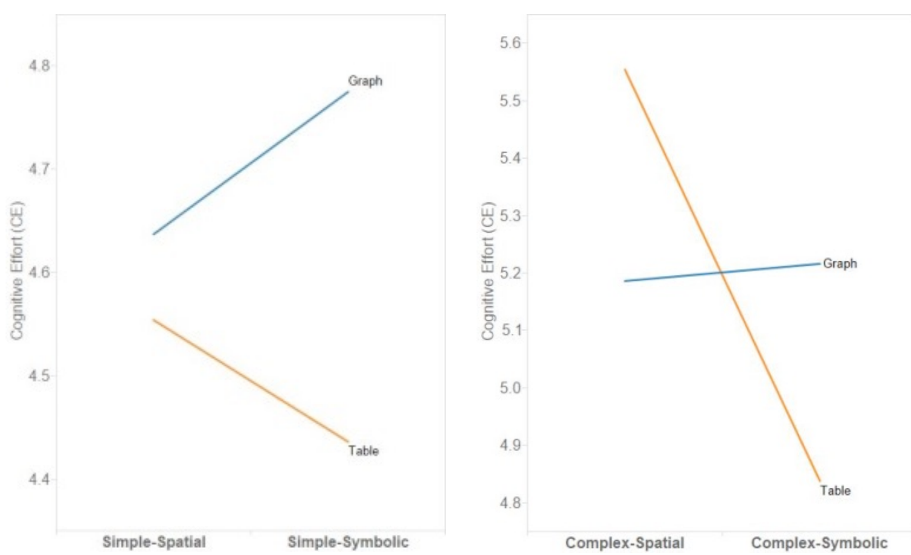

Figure 1. Pairwise Comparison Between Tasks

A pairwise comparison[3] of CE mean difference (see Table 6) between the simple spatial task with graphs (cell 1; M = 4.554; SD = 0.150) and the simple spatial task with tables (cell 2; M = 4.637; SD = 0.150) (i.e., .083; SD = 0.212) was not significant (p = 0.350); therefore, we did not find support for H1. A pairwise comparison of CE mean difference between the simple symbolic task with graphs (cell 3; M = 4.775; SD = 0.150) and the simple symbolic task with tables (cell 4; M = 4.436; SD = 0.150) (i.e., -.338; SD = 0.212) approached but did not reach significance (p = 0.066); therefore, we did not find support for H2. A pairwise comparison of CE mean difference between the complex spatial task with graphs (cell 5; M = 5.186; SD = 0.150) and the complex spatial task with tables (cell 6; M = 5.554; SD = 0.150) (i.e., -0.368) was significant (p = 0.034); therefore, we found support for H3. Lastly, a pairwise comparison of CE mean difference between the complex symbolic task with graphs (cell 7; M = 4.838; SD = 0.150) and the complex symbolic task with tables (cell 8, M = 5.216; SD = 0.150) (i.e., -.377) was significant (p = 0.031); therefore, we found support for H4. Table 7 summarizes these findings.

Table 7. Summary of Findings

Hypotheses	Exp. cells	Diff. in CE	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

We conducted regression tests to test H5 through H8. We found that CE had statistically significant direct impact on time for both simple (adjusted R square = 5.1%, F(136) = 10.252, p = 0.002) and complex (adjusted R square = 6.4%, F(136) = 8.254, p = 0.005) tasks. However, we found that CE effect had no effect on accuracy for either simple or complex tasks. Table 8 shows the regression results, and Table 9 summarizes our findings.

Table 8. Regression Results

	Simple tasks		**Complex tasks**	
	H5	H6	H7	H8
	Time	Accuracy	Time	Accuracy
Constant	18.816 (15.765)	1.103 (.173)	23.219 (41.032)	0.579 (.268)
Cognitive effort (CE)	9.656*** (3.361)	-.044 (.037)	24.942*** (7.790)	-.019 (.051)
R square	0.241	0.103	0.267	0.033
Adjusted R square	0.051	0.003	0.064	0.033
No of Observations	136		136	
We note standard error in parentheses. **,*** indicates significance at the 95% and 99% level, respectively.				

[3] We conducted a pairwise comparison of direction and statistical significance of mean difference for cells 2 – 1, 3 – 4, 6 – 5, and 7 – 8 (see Table 6) to evaluate H1 through H4 using Fisher's LSD method for multiple comparison. Because H1 to H4 are theory-supported directional hypotheses, we adopted one-tail significance in interpreting the results.

Table 9. Summary of Findings

Hypotheses	Findings
H5: For simple tasks, increase in cognitive effort increases the amount of time that a decision maker needs to make a decision.	Supported
H6: For simple tasks, increase in cognitive effort is associated with a decrease in decision accuracy.	Not supported
H7: For complex tasks, increase in cognitive effort increases the amount of time that a decision maker needs to make a decision.	Supported
H8: For complex tasks, increase in cognitive effort is associated with a decrease in decision accuracy.	Not supported

6 Discussions and Implications

As a response to a gap in the literature and due to CFT's value in today's data-driven decision making environment, we investigate cognitive effort, the theorized mechanism central to cognitive fit, in this study. More specifically, we evaluate how the match between task type and representation format impacts cognitive effort and how cognitive effort impacts decision performance. CFT proposes that cognitive effort represents the mechanism that fit impacts and the variable that drives decision making performance. We designed our study to evaluate such suggestions through eight hypotheses across two levels of task complexity: simple and complex. In this context, several new findings about cognitive effort emerged.

First, participants did not perceive significant change in cognitive effort in simple tasks with the two different formats (tabular and graphical) but did perceive it for more complex tasks. More specifically, for simple tasks, they did not perceive a significant difference in cognitive effort regardless of whether they dealt with information formats that represented theorized cognitive fit or not. Although this finding does not support our hypotheses for simple tasks, we might explain the results by evaluating participants' performance relative to time and accuracy and by comparing it with other empirical research results. In a post hoc analysis (pairwise analysis) for both decision time (for spatial and symbolic tasks) and accuracy (the spatial task only), we found that participants did not perform significantly differently in different formats (see Table 10).

Table 10. Post Hoc Analysis: CE in Simple Tasks

	Time	Accuracy
Task type	**Mean difference (Sig)**	**Mean difference (Sig)**
Simple spatial	-5.677 (0.528)	.000 (1)
Simple symbolic	-9.971 (0.268)	.235 (0.005)

As for why, the evaluated tasks may have been too simple to cause a substantial difference in participants' speed and accuracy performance. Other researchers have suggested this explanation in the past (Vessey, 1991). In our literature review, we noted several other studies that failed to confirm similar hypothesis as well. In our study, however, we can go a step further and assert that users' inability to perceive a significant difference in cognitive effort accompanied task-representation fit's inability to result in performance advantages (time and accuracy) over an alternative format (lack of task-representation fit). Therefore, considering the post hoc analysis, our results for simple tasks do not contradict CFT but instead provide some degree of empirical support for the role of cognitive effort. On the other hand, these findings do elevate concerns about the extensive reliance on CFT-based hypotheses in simple tasks in the IS literature.

However, we found that task-representation fit did impact participants' perception of cognitive effort differently for complex tasks than for simple tasks. For complex tasks, we found that task-representation fit impacted cognitive effort as we hypothesized. In other words, participants reported lower cognitive effort when they solved complex spatial tasks through spatial (graphical) rather than tabular (table) formats. Similarly, they reported lower cognitive effort when they solved a complex symbolic task through tabular (tables) rather than spatial (graphs) formats. To further interpret our findings, we also conducted post hoc analysis for only complex tasks and found that, for both decision time (symbolic tasks only) and accuracy (both symbolic and spatial task), participants performed significantly differently across fit/no fit conditions (see Table 11).

Table 11. Post Hoc Analysis: CE in Complex Tasks

	Time	Accuracy
Task type	**Mean difference (Sig)**	**Mean difference (Sig)**
Complex spatial	-21.457 (0.116)	.235294 (0.026)
Complex symbolic	-32.68953 (0.035)	.205882 (0.044)

Therefore, in the CFT context, our research provides the first empirical evidence that change in cognitive effort accompanies a change in decision performance. Combined with findings for simple tasks, our findings suggest that, once a task becomes sufficiently complex, individuals can detect a difference in cognitive effort between fit/no-fit inducing representations.

Second, the relationship between cognitive effort and traditional decision performance measures may not be as straightforward as CFT suggests. For example, unlike in the case of simple spatial tasks, for simple symbolic tasks, the participants did have significant variance in accuracy due to a difference in presentation format, while, at the same time, they did not report the difference in cognitive effort. Studies that do not measure cognitive effort yet claim it as the underlying mechanism for cognitive fit's impact on performance would miss this nuanced discovery. We might explain this surprising finding in several ways. On one hand, as in three instances of the simple tasks (see Table 10), cognitive fit's weak impact on cognitive effort perception may have arisen because the simplicity of the problem itself regardless of accuracy performance may result in such a small difference in cognitive efforts that it makes it hard for one to detect perceptually. In other words, one may not be able to clearly link a perceived measure of effort and more objective measure of accuracy for simple tasks. Alternatively, one may need to consider other factors that potentially influence cognitive effort across different contexts, factors such as personal traits (need for cognition, graphical skills, domain knowledge, experience) or group-based factors (organizational, societal, cultural). Lastly, since cognitive fit had a poor impact on cognitive effort perception only for the symbolic tasks, a task's nature (spatial, symbolic) could have its own impact on the alignment between effort and accuracy in the context of simple tasks.

Interestingly, in one complex task scenario (complex spatial), participants did not have significant variance in time due to a difference in presentation format (fit) while, at the same time, reported a difference in cognitive effort. This finding may indicate that, as task complexity increases, individuals do not view the same amount of time on a decision as "equal". In the case of complex spatial task, our participants worked for a similar duration across formats but reported working "harder" when using tables over graphs. CFT-based research could miss such findings if it continues to focus solely on representation-task fit and decision performance in terms of time and accuracy. Regardless of the explanation, the above findings do suggest a need for a more nuanced approach in task-representation fit (cognitive fit) research. At a minimum, studies need to start measuring cognitive effort because their focus on the "usual" outcomes (time and accuracy) may downplay or misinterpret the cost of processing (cognition). We should augment performance measures with perceptual measures, especially perceived effort, to understand CFT in a more holistic way.

Third, as expected, cognitive effort influenced time performance for both simple and complex tasks (H5 and H7). This finding suggests that, once users do experience varying levels of effort, it does impact their efficiency as CFT indicates. However, and more interestingly, our study provides initial evidence that this insight differs across task nature; in a post hoc analysis, we found that, for simple tasks, the relationship between cognitive effort and time was more pronounced for symbolic tasks, while, for complex tasks, it was more pronounced for spatial tasks. Although we did not expect this difference across tasks, our post hoc results about task-presentation fit's influence on time for complex spatial tasks may explain it.

Fourth, for performance accuracy (H6 and H8), we found no evidence of a relationship between cognitive effort and performance. Our findings suggest that individuals who solve a simple task do not appear to start to optimize effort and accuracy but will work on the problem harder and work through it to solve the problem more accurately. Thus, our findings do not support the premise that an increase in effort due to task-representation misfit will result in degraded performance accuracy for simple tasks. Similarly, prior research has reported a difficulty in linking presentation formats to accuracy for complex tasks (Frownfelter-Lohrke, 1998; Speier, 2006; Vessey & Galletta, 1991), and we found similar results. However, we do provide initial empirical evidence that there is a lack of link between perceived cognitive effort and performance accuracy and suggest a need to reassess other important factors that may drive these results, such as task difficulty as the missing independent variable and effort and accuracy as outcomes. Consequently, the increase in effort may both indicate cognitive misfit (leading to lower accuracy) and result from a willingness to exert effort to deal with difficulty (leading to higher accuracy), which may result in higher variance in results and potentially explains why we found non-significant correlations between effort and accuracy. Lastly, and considering our findings for H5 and H7, these results may arise from the two competing forces that we discuss in Section 3. Individuals who expend more effort and time on transforming and extracting information may better comprehend it and, thus, improve their accuracy, which could partially cancel the decrease in accuracy due to increase in cognitive effort that arises from lack of cognitive fit as CFT argues.

In summary, from a theoretical perspective, our novel focus on cognitive effort incrementally extends the well-researched cognitive fit phenomenon. CFT represents an influential and widely used IS theory. Its early success and ability to predict performance resulted in the IS research community's quickly adopting it for various display formats, problem tasks, and contextual domains. Although rooted in other disciplines, CFT represents a rare IS native theory that will most likely continue to influence IS research. As such, our research reexamines a phenomenon that is salient to the IS community while providing a compelling rationale to focus on cognitive effort's role in CFT and to directly measure it.

From a practical perspective, future research should evaluate our study in the context of how practitioners use business intelligence (BI) visual components, such as dashboards and visual data displays. Although the clear majority of business users have never received training in data visualization design, in this age of self-service dashboards and data analyses, they can use a single mouse click to transform or alternatively display data with minimal computer processing or personal cost. The ease with which users can author and modify data displays may transfer authoring/processing costs from the visualization designer/author to the consumer and decision maker. Consequently, they may change the way they understand data and, subsequently, make decisions. For that reason, we need to critically evaluate the usefulness and appropriateness of visual data displays and the role of cognitive effort in that context. Therefore, we consider our empirical findings as a call for research to better understand cognitive effort a critical first step in that evaluation process.

7 Limitations and Future Research

As with most research, our study has several limitations that present opportunities for further research. First, given the strong theoretical foundation, we did not expect our regression results. The highest level of explained variance was 6.4 percent, and only two of the four regression models were statistically significant. Given the strong reliance on cognitive effort mechanism's strong theoretical role in the CFT-based literature (see quotes in Section 2.1) and given that we adopted three out of four tasks from the existing literature, the low level of explained variance raises important questions about cognitive effort, its role, and measurement. We assert that our results represent two calls to action. On the one hand, the difficulty we faced in measuring cognitive effort could explain the relatively low variance or lack of statistical significance we found in our results. Although we used a pioneering method to evaluate and measure cognitive effort in the CFT context, we measured cognitive effort perceptually. While perceptual measures remain the dominant way to assess user experiences in IS research, we suggest a need to continue describing, understanding, and capturing cognitive effort. Our findings suggest that we must be careful not to rely exclusively on perceptual and subjective measures of cognitive effort. Users do not always consciously recognize their cognitive decision making process when relying on visualizations (Yetgin, Jensen, & Shaft, 2015). Furthermore, users might be unable, uncomfortable, or unwilling to accurately self-report IS constructs that make up cognitive processes, such as cognitive strain or effort (Dimoka et al., 2012). Cognitive effort represents a complex phenomenon that may require multiple and more complex methods to measure. One such way may come from adopting more objective measures of cognitive effort through biometrics. Human-computer interaction and neuroIS offer promising avenues to measure cognitive effort through eye-tracking, facial expressions, brain activity, and skin and heart response (Bačić, 2018; Bačić & Fadlalla, 2016; Dimoka et al., 2012). This research direction would not only enrich our understanding of cognitive effort but also address a concern that human perception of cognitive effort does not always represent the best way to measure experienced cognitive effort. Investigating alignment, complementarity, or potential paradoxes between perceived ("subjective") versus biometrically measured ("objective") cognitive effort across data displays and task context may provide a promising IS research stream.

On the other hand, factors that influence decision performance other than or in addition to cognitive effort may explain the relatively low explained variance we found. While we purposefully limited the factors we examined to narrow our study's scope to CFT's original context, continued focus on only primarily cognitive effort as the determinant of decision performance may lead one to omit important findings. Our findings suggest that, in future CFT-based studies, researchers should not exclusively rely on the theorized role that cognitive effort has in decision performance when developing hypotheses but consider the potential role that other mechanisms may have in it as well, such as affective (stress, emotions), cognitive (approach/avoidance, engagement, boredom, need for cognition, memory), perceptual mechanisms (preattentive attributes, Gestalt Laws, storytelling), and user biases.

Second, as studies have done in the past, we used a student population for our experiments. Although this practice has become the de-facto norm in IS research, we suggest the need to continue this research using more varied population segments.. We recognize that, in other decision making contexts, research that considers other population segments may prove more important. As such, readers should generalize our findings to other demographic with caution.

Third, the size of our experimental sample may have limited our ability to find significant support for more hypotheses. Although we deployed a highly controlled environment such that we could detect cognitive effort level, a universal human trait, a study with a larger sample could more broadly confirm and/or extend our findings.

Fourth, while highly controlled experiments provide an appropriate environment to measure treatment effects, one may not be able to generalize our findings to a more realistic decision making scenario. Professionals make decisions in an environment that lacks as much control as the one we examined and often includes interruptions, group decision making, time constraints, emotion, managerial biases, and varied screen and display sizes. Since we addressed the fundamental CFT mechanism in this study, we believe a controlled environment represented an appropriate context, but we also recommend subsequent research to contextualize our findings in more realistic settings.

Fifth, we used specific tasks and representation formats (tables, line and bar charts) in our study. With the proliferation of new representation formats (bullet graphs, network diagrams), the integration of older graphical methods with standard BI offerings (maps, histograms, scatterplots), and the emergence of more “exotic” displays (various three dimensional (3D) formats, word clouds, bubble charts) and questionable practices (“chartjunk”), we invite more research to evaluate task-representation fit and consequential cognitive effort using other tasks and other representations formats.

Sixth, one should interpret our results with caution because we removed two items (time and complexity) from the original cognitive strain scale (Cooper-Martin, 1994). Thus, some confounding issues could have emerged because the original cognitive strain items (including time and complexity) belong to the same scale. CFT-based research would benefit from future research that focused on exploring ways to better understand and delineate cognitive effort connected to task duration from task difficulty.

Finally, we limited our scope to only two measures of decision performance: time and accuracy. We did so purposefully to remain aligned with the original studies that form the foundation for CFT. However, organizations also find other decision performance criteria besides time and accuracy as useful in decision making. As such, researchers should conduct studies that investigate how fit and cognitive effort impact other decision-performance measures (such as creativity, confidence, or trust) and/or simultaneous impact across various measures.

8 Concluding Remarks

In summary, in this research, we explore and expand further our understanding about how data representation and task variables impact decision performance by focusing on the cognitive effort mechanism. Unlike prior CFT-based literature that has theorized only about how cognitive effort mechanism impacts decision performance, we directly capture this mechanism as a perceptual measure. As such, this study represents the first to examine how a fit between task type and representation format impacts perceived cognitive effort and how that underlying CFT mechanism impacts decision time and accuracy. We hope that our research stimulates constructive debate around cognition, enhance our understanding of cognitive effort, and further increases the relevance of CFT in the business decision making and data representation context. This study represents only an initial step, and we invite others to further explore the role of cognition, its measurement, and its effects on decision performance.

Acknowledgments

We thank Dennis Galletta, Teresa Shaft, and the blind review team for their guidance and feedback.

References

Abbasi, A., Sarker, S., & Chiang, R. H. L. (2016). Big data research in information systems: Toward an inclusive research agenda. *Journal of the Association for Information Systems*, *17*(2), i-xxxii.

Adipat, B., Zhang, D., & Zhou, L. (2011). The effects of tree-view based presentation adaptation on mobile Web browsing. *MIS Quarterly, 35*(1), 99-122.

Agarwal, R., Sinha, A. P., & Tanniru, M. (1996). Cognitive fit in requirements modeling: A study of object and process methodologies. *Journal of Management Information Systems, 13*(2), 137-162.

Bačić, D. (2018). Biometrics and business information visualization: research review, agenda and opportunities. In F. H. Nah & B. Xiao (Eds.), *HCI in business, government, and organizations* (LNCS vol. 10923, pp. 671-686).

Bačić, D., & Fadlalla, A. (2016). Business information visualization intellectual contributions: An integrative framework of visualization capabilities and dimensions of visual intelligence. *Decision Support Systems, 89*, 77-86.

Baker, J., Jones, D. R., & Burkman, J. (2009). Using visual representations of data to enhance sensemaking in data exploration tasks. *Journal of the Association for Information Systems, 10*(7), 533-559.

Beach, L. R., & Mitchell, T. R. (1978). A contingency model for the selection of decision strategies. *Academy of Management Review, 3(3)*, 439-449.

Bettman, J. R., Johnson, E. J., & Payne, J. W. (1990). A componential analysis of cognitive effort in choice. *Organizational Behavior and Human Decision Processes, 45*(1), 111-139.

Bresciani, S., & Eppler, M. J. (2015). The pitfalls of visual representations. *SAGE Open, 5*(4).

Cardinaels, E. (2008). The interplay between cost accounting knowledge and presentation formats in cost-based decision-making. *Accounting, Organizations and Society, 33*(6), 582-602.

Chan, H. C., Goswami, S., & Kim, H.-W. (2012). An alternative fit through problem representation in cognitive fit theory. *Journal of Database Management, 23*(2), 22-43.

Chandra, A., & Krovi, R. (1999). Representational congruence and information retrieval: Towards an extended model of cognitive fit. *Decision Support Systems, 25*(4), 271-288.

Christensen-Szalanski, J. J. J. (1980). A further examination of the selection of problem-solving strategies: The effects of deadlines and analytic aptitudes. *Organizational Behavior and Human Performance, 25*(1), 107-122.

Cooper-Martin, E. (1994). Measures of cognitive effort. *Marketing Letters, 5*(1), 43-56.

DeBois, P. (2015). How to make the most of self-service dashboards. *CMS Wire*. Retrieved from http://www.cmswire.com/analytics/how-to-make-the-most-of-self-service-dashboards/

Dennis, A. R., & Carte, T. A. (1998). Using geographical information systems for decision making: Extending cognitive fit theory to map-based presentations. *Information Systems Research, 9*(2), 194-203.

Dilla, W. N., Janvrin, D. J., & Jeffrey, C. (2013). The impact of graphical displays of pro forma earnings information on professional and nonprofessional investors' earnings judgments. *Behavioral Research in Accounting, 25*(1), 37-60.

Dimoka, A., Banker, R. D., Benbasat, I., Davis, F. D., Dennis, A. R., Gefen, D., Gupta, A., Ischebeck, A., Kenning, P., Pavlou, P. A., Müller-Putz, G., Riedl, R., vom Brocke, J., & Weber, B. (2012). On the use of neurophysiological tools in IS research: Developing a research agenda for neuroIS. *Management Information Systems Quarterly*, 36(3), 679-702.

Dunn, C., & Grabski, S. (2001). An investigation of localization as an element of cognitive fit in accounting model representations. *Decision Sciences, 32*(1), 55-94.

Einhorn, H. J., & Hogarth, R. M. (1981). Behavioral decision theory: Processes of judgment and choice. *Annual Review of Psychology, 32(1)*, 53-88

Few, S. (2013). A pie in the face for information visualization research. *Perceptual Edge*. Retrieved from http://www.perceptualedge.com/blog/?p=1492

Frownfelter-Lohrke, C. (1998). The effects of differing information presentations of general purpose financial statements on users' decisions. *Journal of Information Systems, 12*(2), 99-107.

Gartner. (2016). *Magic quadrant for business intelligence and analytics platforms.* Retrieved from https://www.gartner.com/doc/3200317/magic-quadrant-business-intelligence-analytics

Giboney, J. S., Brown, S. A., Lowry, P. B., & Nunamaker, J. F., Jr. (2015). User acceptance of knowledge-based system recommendations: Explanations, arguments, and fit. *Decision Support Systems, 72*, 1-10.

Goswami, S., Chan, H. C., & Kim, H.-W. (2008). The role of visualization tools in spreadsheet error correction from a cognitive fit perspective. *Journal of the Association for Information Systems, 9*(6), 321-343.

Hong, W., Thong, J. Y. L., & Kar Yan, T. (2004). The effects of information format and shopping task on consumers' online shopping behavior: A cognitive fit perspective. *Journal of Management Information Systems, 21*(3), 149-184.

Howson, C. (2010). Advanced visualization moves to top of mind at TDWI. *InformationWeek*. Retrieved from https://www.informationweek.com/software/information-management/advanced-visualization-is-top-of-mind-at-tdwi/d/d-id/1091838?

Huang, L., Tan, C.-H., Ke, W., & Wei, K.-K. (2013). Comprehension and assessment of product reviews: A review-product congruity proposition. *Journal of Management Information Systems, 30*(3), 311-343.

Hubona, G. S., Everett, S., Marsh, E., & Wauchope, K. (1998). Mental representations of spatial language. *International Journal of Human-Computer Studies, 48*(6), 705-728.

Johnson, E. J., & Payne, J. W. (1985). Effort and accuracy in choice. *Management Science, 31*(4), 395-414.

Kahneman, D. (1973). *Affection and effort*. Englewood Cliffs, NJ: Prentice Hall.

Kamis, A., Koufaris, M., & Stern, T. (2008). Using an attribute-based decision support system for user-customized products online: An experimental investigation. *MIS Quarterly, 32*(1), 159-177.

Khatri, V., Vessey, I., Ram, S., & Ramesh, V. (2006). Cognitive fit between conceptual schemas and internal problem representations: The case of geospatio-temporal conceptual schema comprehension. *IEEE Transactions on Professional Communication, 49*(2), 109-127.

Khatri, V., Vessey, I., Ramesh, V., Clay, P., & Park, S.-J. (2006). Understanding conceptual schemas: Exploring the role of application and IS domain knowledge. *Information Systems Research, 17*(1), 81-99.

Klein, N. M., & Yadav, M. S. (1989). Context effects on effort and accuracy in choice: An enquiry into adaptive decision making. *Journal of Consumer Research, 15(4)*, 411-421.

Li, P., Santhanam, R., & Carswell, C. M. (2009). Effects of animations in learning—a cognitive fit perspective. *Decision Sciences Journal of Innovative Education, 7*(2), 377-410.

McGrath, J.E. (1984.). *Groups: Interaction and performance*. Englewood Cliffs, NJ: Prentice-Hall.

Mennecke, B. E., Crossland, M. D., & Killingsworth, B. L. (2000). Is a map more than a picture? The role of SDSS technology, subject characteristics, and problem complexity on map reading and problem solving. *MIS Quarterly, 24*(4), 601-629.

Navon, D., & Gopher, D. (1979). On the economy of the human-processing system. *Psychological Review, 86*(3), 214-255.

Norman, D. A., & Bobrow, D. G. (1975). On data-limited and resource-limited processes. *Cognitive Psychology, 7*(1), 44-64.

Nunnally, J.C. (1978). *Psychometric theory* (2nd Ed.). New York: McGraw-Hill.

Russo, J. E., & Dosher, B. A. (1983). Strategies for multiattribute binary choice. *Journal of Experimental Psychology: Learning, Memory, and Cognition, 9*(4), 676-696.

Shaft, T. M., & Vessey, I. (2006). The role of cognitive fit in the relationship between software comprehension and modification. *MIS Quarterly, 30*(1), 29-55.

Shen, M., Carswell, M., Santhanam, R., & Bailey, K. (2012). Emergency management information systems: Could decision makers be supported in choosing display formats? *Decision Support Systems, 52*(2), 318-330.

Shugan, S. M. (1980). The cost of thinking. *Journal of Consumer Research, 7*(2), 99-111.

Simon, P. (2014). The visual organization: Data visualization, big data, and the quest for better decisions. *Harvard Business Review*. Retrieved from https://hbr.org/2014/06/the-visual-organization-data-visualization-big-data-and-the-quest-for-better-decisions

Sinha, A. P., & Vessey, I. (1992). Cognitive fit: An empirical study of recursion and iteration. *IEEE Transactions on Software Engineering, 18*(5), 368-379.

Speier, C. (2006). The influence of information presentation formats on complex task decision-making performance. *International Journal of Human-Computer Studies, 64*(11), 1115-1131.

Speier, C, Vessey, I., & Valacich, J. S. (2003). The effects of interruptions, task complexity, and information presentation on computer-supported decision-making performance. *Decision Sciences, 34*(4), 771-797.

Teets, J. M., Tegarden, D. P., & Russell, R. S. (2010). Using cognitive fit theory to evaluate the effectiveness of information visualizations: An example using quality assurance data. *IEEE Transactions on Visualization & Computer Graphics*, *16*(5), 841-853.

Thomas, E. A. (1983). Notes on effort and achievement-oriented behavior. *Psychological Review, 90*(1), 1-20.

Umanath, N. S., & Vessey, I. (1994). Multiattribute data presentation and human judgment: A cognitive fit perspective. *Decision Sciences, 25*(5/6), 795-824.

Vessey, I. (1994). The effect of information presentation on decision making: A cost-benefit analysis. *Information & Management, 27*(2), 103-119.

Vessey, I. (1991). Cognitive fit: A theory-based analysis of the graphs versus tables literature. *Decision Sciences, 22*(2), 219-240.

Vessey, I., & Galletta, D. (1991). Cognitive fit: An empirical study of information acquisition. *Information Systems Research, 2*(1), 63-84.

Wood, R. E. (1986). Task complexity: Definition of the construct. *Organizational Behavior and Human Decision Processes, 37*(1), 60-82.

Wright, P. (1975). Consumer choice strategies: Simplifying Vs. optimizing. *Journal of Marketing Research, 12*(1), 60-67.

Yetgin, E., Jensen, M. L., & Shaft, T. M. (2015). Complacency and Intentionality in IT use and continuance. *AIS Transactions on Human-Computer Interaction*, *7*(1), 17-42.

Appendix A: Complex Spatial Task: Graphical & Tabular Representation

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%

Figure A2. Complex Spatial Task

Ratio Analysis

Company	Return on Assets	Return on Stockholders Equity	Current Ratio	Debt-to-Equity	Debt-to-Total Assets	Gross Profit %	Profit Margin %
Company A	0.167	0.538	150%	2.231	0.690	0.309	0.130
Company B	0.100	0.400	111%	3.000	0.750	0.278	0.111
Company C	0.094	0.375	120%	3.000	0.750	0.220	0.100
Company D	0.168	0.840	135%	4.000	0.800	0.484	0.135
Company E	0.186	1.267	116%	6.833	0.864	0.369	0.173
Company F	0.063	0.250	103%	3.000	0.750	0.333	0.095

EPS Trend by Company

	Year of Year										
Company	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	20
Company A	2.340	2.500	2.060	2.880	2.700	2.850	2.700	2.500	2.454	2.545	3.6
Company B	1.007	0.967	1.067	1.020	1.040	1.000	1.160	1.093	1.000	1.227	1.3
Company C	1.560	1.500	1.740	1.640	1.500	1.840	1.500	1.740	1.640	1.500	1.5
Company D	2.850	2.950	2.650	3.390	3.260	3.150	3.440	3.140	2.954	3.385	4.2
Company E	3.070	2.950	3.340	3.170	3.060	3.340	3.240	3.380	3.140	3.340	3.8
Company F	1.040	1.000	1.160	1.093	1.000	1.227	1.000	1.160	1.093	1.000	0.6

Return Analysis

Company	Return on Assets	Target Return on Assets	Return on Stockholders Equity	Target Return on Stockholders Equity
Company A	0.167	0.0625	0.538	0.500
Company B	0.100	0.0625	0.400	0.500
Company C	0.094	0.0625	0.375	0.500
Company D	0.168	0.0625	0.840	0.500
Company E	0.185	0.0625	1.267	0.500
Company F	0.063	0.0625	0.250	0.500

Sales Trend by Company

	Year of Year										
Company	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	20
Company A	225,000	278,000	240,000	275,000	285,000	280,000	295,000	300,000	275,000	285,000	270,0
Company B	103,000	114,000	134,500	120,000	143,000	150,000	165,000	154,400	165,000	156,000	180,0
Company C	143,000	150,000	165,000	154,400	165,000	156,000	150,000	165,000	154,400	165,000	150,0
Company D	192,000	222,000	238,500	259,000	272,000	280,000	285,000	292,000	300,000	305,000	310,0
Company E	110,000	128,000	143,500	150,000	152,000	164,000	179,000	183,400	183,400	185,000	220,0
Company F	91,000	93,000	96,000	96,750	97,500	98,200	99,000	99,500	99,750	101,000	105,0

Figure A2. Tabular Representation for Complex Spatial Task

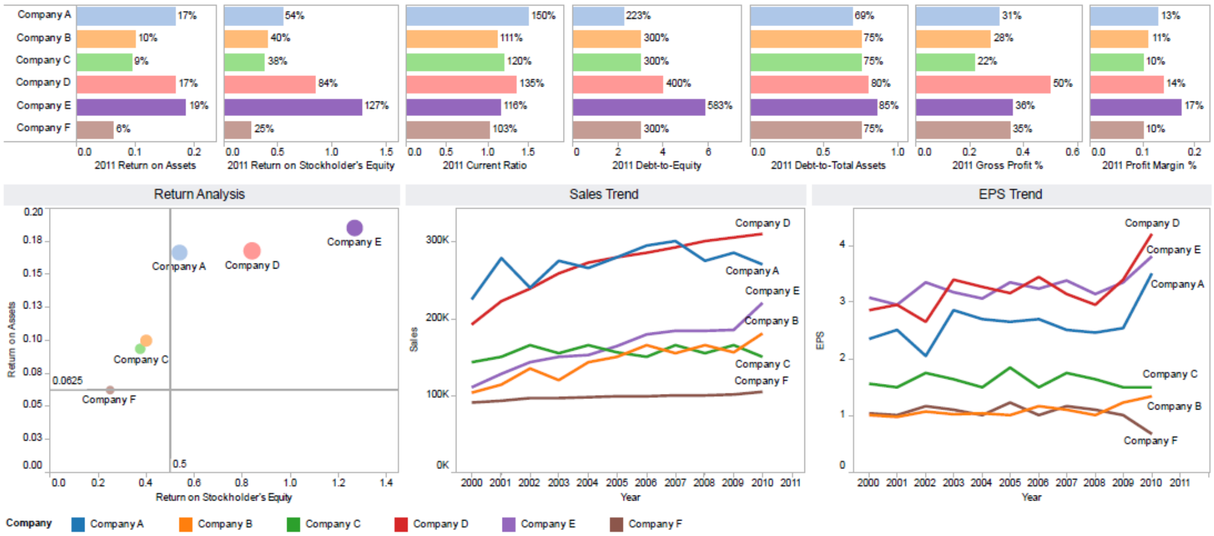

Figure A3. Graphical Representation for Complex Spatial Task

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