An Alternative Fit through Problem Representation in Cognitive Fit Theory

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ABSTRACT
This paper uses cognitive fit theory to analyze the problem solving process in spreadsheet analyses. Cognitive fit theory proposes the formation of mental representation as a part of the problem solving process. However, there is little research examining mental representation, which is a key concept in cognitive fit theory. This study examines the formation of mental representation and proposes an alternative mechanism of cognitive fit between different problem representations and their corresponding mental representations when the task is invariant, but the problem representation changes. Mental representation is then empirically assessed based on the application of Hick’s law, which states that the response time of users making a choice varies with the logarithm of the number of possible choices. Therefore, this study contributes to research on cognitive fit theory by proposing an alternative fit and by demonstrating a feasible approach for identifying mental representations. It contributes to spreadsheet research by showing how problem representations affect task performance in the case of spreadsheet error correction.

Keywords: Cognitive Fit Theory, Hick’s Law, Mental Representation, Problem Solving Process, Spreadsheet

INTRODUCTION
Cognitive fit theory (Vessey, 1991) is widely used to analyze problem-solving performance in decision-making problems, such as for comparing different data presentation formats (e.g., tables and graphs), for different multi-attribute data presentations, and for various problem domains such as accounting, software maintenance, requirements modeling in systems development and spreadsheet error correction (Dennis & Carte, 1998; Dunn & Grabski, 2001; Smelcer & Carmel, 1997; Agarwal, Sinha, & Tanniru, 1996; Shaft & Vessey, 2006; Umanath & Vessey, 1994; Vessey, 1994; Vessey & Galletta, 1991). Problem solving performance in cognitive fit theory is an outcome of the fit between problem representation and task, both of which are characterized by the information they emphasize.

Task in cognitive fit theory refers to the problem-solving task that the user has to per-
form, while problem representation refers to the way in which the information pertaining to the task is presented to the user. For instance, in the context of spreadsheet analysis, the task could be identifying precedent or dependent cells referred to in formulas or calculating cell values given a formula; while the problem representation could be the format in which the spreadsheet data is presented to the user. When the cognitive processes used to act on the problem representation match those used to complete the task, cognitive fit is said to exist, resulting in superior problem solving performance (Agarwal, De, & Sinha, 1999; Vessey, 1991). In order to capture the problem solving process, cognitive fit theory conceptualizes “mental representation”, which is determined by the information requirements of the task and the information emphasized by the problem representation. Mental representation is an important step in the problem solving process underlined by cognitive fit theory; however there is significantly less understanding on mental representation. Current research on cognitive fit theory assumes that mental representations exist, without further validations. Therefore, the need to examine mental representation instead of simply measuring performance outcome (e.g., Shaft & Vessey, 2006) has been highlighted.

Both cognitive fit theory and its extension (which examines the fit between two different mental representations resulting from two different tasks) proposed by Shaft and Vessey (2006) focus primarily on the task and its implications on the formation of mental representation and subsequent cognitive fit. Therefore, an investigation towards assessing mental representation and ways of examining it has so far been unaddressed in the cognitive fit literature. We address this gap by proposing the alternative fit, which is a fit between different components of a problem representation. The essential difference from the original cognitive fit theory is that the alternative fit focuses on the problem representation rather than on the role of task. This is an important distinction given that representational features of the problem have important implications on analysis and performance for the same given task (Hahn & Kim, 1999).

In the alternative fit proposed here, we demonstrate that certain information components of the problem representation are used to create the mental representation, and other components are then used to achieve a fit between the mental representation and the problem representation. This is applicable in a situation where the original cognitive fit does not occur. This study further demonstrates a way of validating the mental representation as manifested in the problem solving process in the context of spreadsheet cell referencing.

Spreadsheet error correction is one among the various problem-solving contexts in which cognitive fit theory has been applied (Goswami, Chan, & Kim, 2008). Spreadsheet errors pose significant business risks to organizations (EUSPRIG, http://www.eusprig.org/), and an alarmingly high number of organizational spreadsheets contain errors (Panko, 2011). Spreadsheets are often ineffectively and inefficiently designed due to a multitude of reasons such as, social, cultural and cognitive reasons (Bhavnani, Peck, & Reif, 2008). Accordingly, significant research effort has been expended in studying spreadsheet error correction (Bishop & McDaid, 2011; Burnett, Sheretov, Ren, & Rothermel, 2002; Chadwick, Knight, & Rajalingham, 2001; Chan, Ying, & Peh, 2000; Clermont, 2003; Davis, 1996; Hendry & Green, 1993; Igarashi, Mackinlay, Chang, & Zellweger, 1998; Lentini, Nardi, & Simonetta, 2000; Rajalingham, Chadwick, Knight, & Edwards, 2000; Sajaniemi, 2000).

The process of spreadsheet error correction still remains tedious and difficult (Goswami et al., 2008; Panko, 1999; Panko & Sprague, 1998; Teo & Lee-Partridge, 1999) because of the cognitive difficulties in comprehending spreadsheets. Since spreadsheet formulas define the interconnections between rows and columns in a spreadsheet, understanding formulas is an essential part in understanding the structure of a spreadsheet. In order to understand formulas, one has to trace cell references in formulas to identify the different cells that make up the
formula (Davis, 1996; Goswami et al., 2008; Hendry & Green, 1993; Sajaniemi, 2000). In this study we select spreadsheet comprehension as the problem domain for examining the alternative fit.

The structure of the paper is as follows: the next section provides the theoretical background for this study by explaining cognitive fit theory, and providing a detailed description of mental representation. The section that follows is devoted towards developing the research hypotheses. It describes the task, problem representations, and how different mental representations are derived, and the notion of alternative fit. Then, we discuss the experimental setup under research methodology. The last three sections focus on data analysis, findings, and their practical and theoretical implications.

THEORETICAL BACKGROUND

Cognitive Fit Theory

The cognitive fit theory (Vessey, 1991; Vessey & Galletta, 1991) asserts that problem solving performance is affected by a fit between a task and a problem representation. The task and the problem representation emphasize certain information which leads to the creation of mental models. A mental model is defined as a representation of something in the human working memory based on certain given premises (Bryne & Johnson-Laird, 1989). Mental models have been found to have significant implications on task performance (Poels, 2011). If the mental model formulated by the problem representation is inconsistent with the mental model formulated by the task representation, then decision making performance may be impeded (Hubona, Everett, Marsh, & Wauchope, 1998). However, mental models that are consistent with the problem representation can result in better understanding and task performance (Poels, 2011). When working with spreadsheets for instance, a mental model could be a representation of the given spreadsheet structure. These mental models are used for actually solving the problem. The more complete the mental model, the better is the user’s understanding of the problem (Masri, Parker, & Gemino, 2008). The mental representation referred to in cognitive fit theory is based on mental models.

Figure 1 depicts the cognitive fit theory, where fit is explained as a match between the information in the task and the information in the problem representation (Vessey, 1991; Shaft & Vessey, 2006). Both fit and the mental representation are abstract constructs (depicted using dotted lines), and are usually not further described nor empirically measured. The implication of fit is better problem solving performance, mostly measured in terms of time taken to perform the task and the number of errors made. In the context of spreadsheet analysis, cognitive fit between task and problem representation has been found to have resulted in better problem solving performance (Goswami et al., 2008). Mental representation on the other hand is a representation of the problem solving process and comprises mental models created based on the task and the problem representation.

Problem Representation

Problem representation refers to the way in which problem related information is presented to the user. In the cognitive fit theory parlance, problem representation plays an important role in task performance since the information emphasized by the problem representation is used in the formation of the mental representation. For instance, for a given task, the problem can be represented in different ways such as presenting data in a graphical or in a tabular format (Vessey & Galletta 1991). Previous research has often focused on using task differences in order to assess cognitive fit. However, in this study we examine the effect of different problem representations while keeping the task invariant.

Mental Representation

Mental representation is the culmination of the process through which users act on the information from the task and the problem representation (Vessey, 1991, 2006). Mental
representation can be viewed from both process perspective and output perspective. From the process perspective, it refers to the cognitive process that people use during comprehension and problem solving (Shaft & Vessey, 2006). The output perspective refers to the creation of the mental perception (or model) of the problem after the cognitive processes have acted (Vessey, 1991). Conceptual modeling is an integral step of dealing with real world problems (Reinhartz-Berger & Sturm, 2008). Accordingly, mental representation is integral to problem solving, and it exists even if cognitive fit does not occur between the task and the problem representation.

Understanding mental representation is therefore an important aspect of understanding the problem solving process. The mental models created using the information elements of the task and the problem representation are used to attain a mental representation of the problem solving task. From a process perspective, mental representation can be considered to be the problem solving process. In this study, the problem solving process is the actual decision making process that involves a decision of picking the correct cell from a screen containing many cells.

HYPOTHESES DEVELOPMENT

Spreadsheet analysis is a task that has high relevance for organizations, and users often face cognitive difficulties while working with spreadsheets (Bhavnani et al., 2008). Spreadsheet analysis requires understanding the structure of the spreadsheet. Cells in a spreadsheet are typically connected through formulas, and understanding the structure of the spreadsheet involves analyzing these formulas and tracing dependencies among cells. Using cognitive fit theory as the theoretical basis, we hypothesize about task performance in the context of spreadsheet analysis.

Task

The spreadsheet analysis task studied in this research is that of locating the precedent cell from a given spreadsheet formula that is displayed after clicking the dependent cell. This task of finding the precedent cell given a dependent cell is also referred to as chaining (Goswami et al., 2008). Spreadsheet cells containing formulas typically refer to other cells within the spreadsheet. For example, if cell C4 within a spreadsheet has the formula “=3*B1”, B1 is the cell referenced by C4 and in spreadsheet terminology (as used in Microsoft Excel) B1 is called the precedent cell of C4 while C4 is called the dependent cell of B1 (Davis, 1996; Goswami et al., 2008).

Prior research has analyzed spreadsheet tasks at higher task levels. For example, Galletta, Hartzel, Johnson, Joseph, and Rustagi (1996) studied error detection with or without
formula display, with paper or screen presentation. Teo and Tan (1999) studied qualitative and quantitative errors. Goswami et al. (2008) investigated the role of visualization tools in the correction of different spreadsheet error types. The task of finding a precedent cell is selected for further investigation in this study as it is a fundamental activity in spreadsheet analysis and has been considered critical in comprehending a spreadsheet model (Galletta, Hartzel, Johnson, Joseph, & Rustagi, 1997; Goswami et al., 2008; Hendry & Green, 1994; Panko, 1999; Saariluoma & Sajaniemi, 1991; Teo & Lee-Partridge, 1999).

The task in this study constitutes identifying and clicking on the precedent cell of a given dependent cell. For example, where the formula in a dependent cell is “=3*B1”, the task involves locating cell B1 and clicking on it. In order to perform this task, users have to visually look at the given problem space (in this case the problem space is the given spreadsheet model) and then find the precedent cell from all the cells that are contained in this space. Therefore, the task consists of the following steps: mentally decide which cell is the response cell, visually locate the response cell on the screen, and physically move the mouse to the selected cell and click on it. This task can be thought of as a visual spatial task, similar to that of finding a location on a map.

**Problem Representation**

The different ways of representing formulas in Microsoft Excel constitute the different problem representations used in this study. This study uses two different problem representations.

**Problem Representation 1: A1 Representation**

In Microsoft Excel, different referencing styles can be used to reference or label rows, columns and cells. One such referencing style is called the“A1” referencing style. In the A1 referencing style, columns are labeled alphabetically from the left and rows are numbered sequentially from the top. Cell names consist of the corresponding column name and the row name. For example, a cell named E8 indicates that it is located in the E column and the 8th row. The same naming technique is used when a particular cell is referenced in a formula. Therefore, if the formula contained in cell E8 is 5*C3, the precedent cell C3 is located in column C and row 3 (Figure 2).

**Problem Representation 2: R1C1 Representation**

In Microsoft Excel’s R1C1 referencing style, both columns and rows are labeled using numbers – columns are numbered sequentially from the left and rows are numbered sequentially from the top. However, formulas referencing precedent cells use a numbering system starting from the dependent cell, where the name of the precedent cell indicate the number of rows and columns that separate the precedent cell from the dependent cell. Continuing with our previous example, the formula would be represented as 5* R[-5]C[-2], which means that the precedent cell is located 5 rows up (the meaning of R[-5]) and 2 columns to the left (the meaning of C[-2]) from the dependent cell (Figure 3).

**Cognitive Fit**

The task in this study is a visual spatial task where users need to identify the location of the precedent cell in the given problem space which contains many cells. Given that problem representation has important implications for task analysis and performance (Hahn & Kim, 1999), problem representation will determine the extent of cognitive effort required by users to mentally process the information contained in it to perform the task.

There are two separate aspects of locating a precedent cell referred in a formula. First, users have to understand the textual cell referencing scheme of the spreadsheet model, and second, they have to understand the textual cell referencing scheme used in the formulas. These understandings will be used to locate the precedent cell.
Both A1 and R1C1 representations do not provide any visual-spatial aids or cues in identifying the precedent cells, and therefore cognitive fit does not occur. However, the amount of mental transformation required to perform the task for each of these representations will differ and therefore there will be differences in the performance levels between the two representations. Previous research has shown that task performance also depends on the strategies adopted to carry out the task (Fern et al., 2010). It is likely that users will use different strategies to perform the task, and these strategies will result in different mental representations. Similar to previous empirical studies using cognitive fit theory (Agarwal et al., 1999, Galletta et al., 2003, Goswami et al., 2008, Hubona et al., 1998, Vessey, 1991), problem solving performance in this research is measured in terms of time taken (i.e., efficiency) and error rate (i.e., effectiveness) (Vessey, 2006).

**Mental Representation and Fit**

Adopting a “process perspective,” this study treats mental representation as the mental process resulting in problem solving. The following section uses Hick’s law to show that the two different problem solving processes can be explained using different equations involving the location of the precedent and dependent cells, and the time taken to decide on the correct precedent cell. This allows us to empirically validate which of the two problem solving processes occur for each problem representation.

In a spreadsheet, location can be indicated in many ways. The problem representations provide the necessary information regarding cell locations. Using the model-theoretic approach towards spatial reasoning which states that people use their understanding of the given information regarding the task at hand to construct a mental model (i.e., a scenario, an image, or a spatial array) and then use it
to reason about the task (Bryne & Johnson-Laird, 1989; Sternberg, 1985), we delineate the mental models created by the problem representations and consequently the mental representations involved in problem solving. The A1 and R1C1 representations consist of two components of information that indicate the location of the precedent cell. These are the spreadsheet cell labeling technique and the referencing scheme used in the formulas. The cell labeling techniques for both representations are similar since they start from the top-left corner and move sequentially to the right and to the bottom. Therefore, this information component is common for both problem representations.

In the A1 representation, since cell names are indicated by the column and row in which the cell is located, and are independent of the dependent cell, the mental model will be based on the A1 cell (i.e., the top-left corner of the spreadsheet). Users will try to locate the precedent cell using the created mental model, by starting to look from the top-left corner. Therefore, the mental representation corresponding to the A1 problem representation is anchored to the A1 cell, and we term this as “A1-anchored” mental representation.

For the R1C1 representation, the name of a precedent cell in a formula indicates its position relative to the dependent cell, and therefore the mental model will be based on the dependent cell and not its absolute row and column number. Thus, in order to locate the precedent cell, users are likely to use the dependent cell as the starting point or anchor to find the precedent cell. Accordingly, the corresponding mental representation will be to start looking from the dependent cell in order to find the precedent cell. Hence we term this as “Dependent-anchored” mental representation.

For both A1-anchored and Dependent-anchored mental representations, performing the task entails selecting a specific cell among a number of possible cells. The steps involved in doing this are – (a) mentally deciding which cell is the precedent cell, (b) visually locating the cell on the screen, and (c) physically moving the mouse on the selected cell and clicking on it. However, these three steps are likely to get intermingled, as both eye and cursor movements are needed to perform step (a) and (b), e.g., mentally decide which cell is the precedent cell.

To validate that the two problem representations indeed give rise to the different mental representations as described in the above paragraphs, we use time taken in performing the task to assess the two mental representations. To derive time taken in the problem solving process, we draw from the areas of experimental psychology and human-computer interaction.

Time Calculation Using Hick’s Law

Research in experimental psychology and human-computer interaction has shown that the time taken to choose a particular target from a number of possible targets can be estimated using Hick’s law (Hick, 1952), which states that the response time of users making a choice varies with the logarithm of the number of possible choices. The equation for Hick’s law can be expressed in the following form: Time taken = constant + b * \log_2(N+1), where N is the number of targets to choose from. It should be noted that Hick’s law is an empirically derived law, and does not depend on any assumption of how the target is selected. The logarithmic term in the above equation however intuitively reflects that people divide the number of choices into sub-categories, and eliminate about half of them in each step, rather than considering each choice one-by-one which would have required linear time (Card, Moran, & Newell, 1983).

Hick’s law is commonly used to study reaction time for choice among alternatives (e.g., Beggs, Graham, Monk, Shaw, & Howarth, 1972; Gignac & Vernon, 2004; Mahurin & Pirozzolo, 1993; Thimbleby, 2004) and has been declared as “one of the most robust regularities that have been reported in the choice response time literature” (Usher, Olami, & McClelland, 2002, p. 704). It was also found that experience does not invalidate Hick’s law (Vickrey & Neuringer, 2000). A later study suggested that the logarithm term can be simplified to \( b \cdot \log_2(N) \) (Howarth,
Beggs, & Bowden, 1971). We use this version for the subsequent calculations.

In the spreadsheet context, a user has to find one cell from among many cells. For the A1-anchored and Dependent-anchored mental representations, users will start looking for the precedent cell by starting their search process from the A1-cell or from the dependent cell respectively and, therefore will have different number of options or possible target cells to make a choice from. To assess which mental representation is formed, we use the time calculated based on Hick’s law for the different number of choices pertaining to each mental representation.

Let \( rp \) and \( rd \) be the row numbers of the precedent cell and the dependent cell respectively, starting from the topmost row. Let \( cp \) and \( cd \) be the column numbers of the precedent cell and dependent cell respectively, starting from the leftmost column.

Let \( rnr \) be the number of rows between the precedent and dependent cells, inclusive, and \( cnr \) be the number of columns between the precedent and dependent cells, inclusive. Thus,

\[
\begin{align*}
    rnr &= |rp - rd| + 1 \\
    cnr &= |cp - cd| + 1
\end{align*}
\]

Let \( rna \) be the number of rows between the precedent cell and cell “A1”, inclusive, and \( cna \) be the number of columns between the precedent cell and cell “A1”, inclusive. Thus,

\[
\begin{align*}
    rna &= rp \\
    cna &= cp
\end{align*}
\]

When users try to locate the precedent cell by starting from the top-left corner of the spreadsheet (i.e., cell “A1”), the number of possible targets is a product of the possible rows and columns (i.e., \( rna \) and \( cna \)). Therefore, based on Hick’s law, the time taken to find the precedent cell can be estimated using Equation 1.

\[
\text{Time} = \text{constant}1 + b1 * \log_2(rna * cna)
\]

(1)

On the other hand, when users try to locate the precedent cell by starting from the dependent cell, the number of possible targets is the total number of cells between the dependent cell and the precedent cell, and can be expressed as a product of \( rnr \) and \( cnr \). Therefore, the time taken to find the precedent cell can be estimated using equation 2.

\[
\text{Time} = \text{constant}2 + b2 * \log_2(rnr * cnr)
\]

(2)

Equations 1 and 2 can be used to assess whether users use the A1-anchored or dependent-anchored mental representation. For the A1 representation, the time taken to find the precedent cell is likely to follow equation 1, and not equation 2. For the R1C1 representation, the time taken to find the precedent cell is likely to follow equation 2, and not equation 1. In summary, based on problem presentations, we hypothesize two different problem solving processes:

H1: For A1 problem representation, users will have an A1-anchored mental representation. That is, the time taken by users will follow the relationship expressed in Equation 1 (i.e., the regression according to Equation 1 will be significant) and will not follow the relationship expressed in Equation 2 (i.e., the regression according to Equation 2 will not be significant)

H2: For R1C1 problem representation, users will have a dependent-anchored mental representation. That is, the time taken by users will not follow the relationship expressed in Equation 1 (i.e., the regression according to Equation 1 will not be significant) and will follow the relationship expressed in Equation 2 (i.e., the regression according to Equation 2 will be significant)
The given task is a visual spatial task; however, the A1 and R1C1 representations are not visual representations of the problem. Therefore, there is a mismatch between the information emphasized by the problem representations and the information requirements of the task, which results in lack of cognitive fit between task and problem representation. However, performance of a task always happens through the formation of a mental representation, and there can be a fit or misfit between the mental representation and information components of the problem representation. We call this the alternative fit, to distinguish it from the usual cognitive fit between task and problem representation. Similar to the cognitive fit, the alternative fit between problem representation and mental representation will result in better performance, and can therefore be examined through various performance measures. We propose:

Proposition: An alternative fit between the problem representation and the mental representation will lead to better task-solving performance.

For the A1 problem representation, the mental model and the corresponding A1-anchored mental representation matches with the spreadsheet cell labeling scheme which also starts with the A1 cell. Therefore, there is no requirement for additional mental transformation to perform the task. This results in a fit between the mental representation and the problem representation and facilitates task performance.

In the R1C1 representation, the mental model and the corresponding mental representation are dependent-anchored, and therefore do not match with the spreadsheet cell-labeling scheme which starts from the top-left corner of the spreadsheet. Therefore, users need to perform cognitive transformation in order to perform the task using the mental representation. For instance, as shown in Figure 3, if the dependent cell is located in the 8th row and 5th column, and the precedent cell is referenced as R[-5]C[-2], then this information is used by users to mentally relabel the rows and columns in the spreadsheet, anchoring (0,0) at the dependent cell. The users then locate the precedent cell by using the spreadsheet relabeling scheme. This mismatch will have a negative impact on task performance.

The A1 problem representation and the corresponding A1-anchored mental representation result in a fit, but the R1C1 representation and the corresponding Dependent-anchored mental representation do not result in such a fit. Therefore, performance will be better for the A1 representation compared to the R1C1 representation. Hence we hypothesize:

H3: Time taken for task performance will be less for the A1 representation than for the R1C1 representation.
H4: Error rate in task performance will be less for the A1 representation than for the R1C1 representation.

Figure 4 summarizes the research design for assessing the mental representation and testing the performance implications of the alternative fit. Both problem representation and mental representation are two-valued constructs. The values for problem representation are A1 and R1C1. Similarly, mental representation takes on two values – “A1-anchored” and “Dependent-anchored”. The A1 representation will result in the “A1-anchored” mental representation, whereas the R1C1 representation will result in the “Dependent-anchored” mental representation. Hypotheses 1 and 2 verify the creation of these mental representations. Performance is measured in terms of time taken to perform the task and the error rate. Hypotheses 3 and 4 are used to assess the alternative fit.

RESEARCH METHODOLOGY

A laboratory experiment was conducted to test the hypotheses. Problem representation is the independent variable that has two values: A1 representation and R1C1 representation. The task was kept unchanged across representations.
Performance is the dependent variable and is measured in terms of the time taken to click on the precedent cell and the error rate.

The experiment involved 73 subjects (56 males, 17 females) aged between 17 and 25. Eighty percent of the subjects had low to medium level of Excel expertise. The other twenty percent had a high level of expertise. All subjects were randomly selected from students who volunteered to participate in the experiment and they were paid about US$20 for their participation. Subjects were given sufficient time to complete the experiment.

Printed instructions were given to the subjects at the beginning of the experiment. Subjects were asked to carefully read through the instructions and were given 15 minutes to do so. Further, all the instructions were then read to the subjects before the experiment. Subjects were allowed to ask questions to clarify any doubt before the experiment. Specific instructions were again displayed on the screen before each spreadsheet session.

A short warm-up exercise consisting of two trials for each representation was given prior to the actual experiment. These trials enabled the subjects to get familiarized with the format of the experiment and helped them in understanding how each representation worked. Subjects were instructed to click on the precedent cell as fast as possible, and at the same time to minimize the number of errors. The software generated a beep when the subject made a mistake by clicking outside the precedent cell, so that the subject could immediately search for the correct cell.

The spreadsheets were shown in two sizes: the Excel default cell size (17 pixels high and 64 pixels wide), and a big cell size (doubled in both height and width). This was done to counter confounding effects arising from subjects changing the screen resolutions or display zooms from the originally provided settings. To avoid complications from multiple screen access, each spreadsheet was limited to one screen. The screen size was 36.5 cm by 27.0 cm with a screen resolution of 1024 by 768 pixels, using 17-inch monitors. Each of the two problems representations was provided in both cell sizes. Subjects worked through two rounds, each with four spreadsheets in the following size sequence: small (one representation), small (the other representation), big (one representation), big (the other representation). While the cell size sequence was kept fixed, the sequence in which representations were presented was randomized across subjects.

The dependent cell was placed at the lower right hand corner of the screen. When subjects clicked on the dependent cell, they could see the formula in either the A1 or R1C1 referencing style, depending on the spreadsheet session. Formulas contained only one precedent cell. The subject had to find and click on the precedent cell. Time was measured (in milliseconds) between the click on the dependent cell and the click on the precedent cell. Clicking anywhere other than the precedent cell was counted as an error. Error rate was the number of error clicks divided by the number of precedent cells in the experiment.

In each spreadsheet, subjects had to work through 20 precedent-dependent cell pairs. At any point of time, subjects were presented with each cell pair, and once they had identified the precedent cell and clicked on it, the next cell pair in a new screen was presented to them. The cell pairs were constant for all subjects, but the sequence of presentation to subjects was
randomized for each subject. The dependent cell is fixed at the lower right hand corner while the precedent cells are scattered, as shown in Figure 5 and Figure 6. There were compulsory rest periods before subjects started working on each spreadsheet. After a subject had finished working through a spreadsheet, he/she was shown the mean time taken for that particular spreadsheet. This method of providing feedback was adopted to enhance the motivation of subjects for optimal performance (Whisenand & Emurian, 1999).

DATA ANALYSIS AND RESULTS

In the experiment each subject received both treatments (A1 and the R1C1 representation). A within-subjects analysis of the data is conducted. The experiment comprised two rounds and performance both in terms of time taken and error rate was better for the second round compared to the first round. This is expected as performance usually improves with experience (Vickrey & Neuringer, 2000). For both rounds, the direction of differences among the presentation styles remained unchanged. In order to simplify the presentation of results, we combined the data from both rounds. Results for default-size and big-size spreadsheets are reported separately. The distributions of time versus distance (from precedent cell to dependent cell) are shown in Figure 7 and Figure 8.

Figure 9 and Figure 10 depict the distribution of errors versus distance between precedent and dependent cells for both default size and big size spreadsheets respectively.

Table 1 summarizes the descriptive statistics of performance (time taken and error rate) for each representation and cell size. The reported time is the average for all clicks. In essence, results are invariant across cell size. Separate reporting serves to highlight the robustness of the results.

Table 2 shows the results of the hypothesis testing regarding mental representations. As described in the preceding section, each spreadsheet (default-cell and big-cell spreadsheets) had 20 precedent cells. The time taken to find

Figure 5. Distribution of precedent cells for default-size spreadsheet
each precedent cell was averaged over all subjects. Further, each precedent cell provided a set of values for rnr, cnr, rna, cna based on its position in the spreadsheet. These values were used for the regressions of equation 1 and 2. Natural logarithm was used instead of logarithm to base two\(^1\). Table 2 reports the results of the regression analysis, for Hypotheses 1 and 2.

For both default-cell and big-cell spreadsheets, H1 is supported, indicating that for the A1 representation, only the A1-anchored mental representation (demonstrated by a significant equation 1) is present and the dependent-anchored mental representation (demonstrated by a non-significant equation 2) is not present. In contrast, for the R1C1 representation, only the dependent-anchored mental representation is present and the A1-anchored mental representation is not present.

In order to investigate H3 and H4, we carry out univariate analysis\(^2\) (with repeated measures) for time taken and error rate. The F and p values are reported in Table 3. The results indicate that fit between problem representation and mental representation leads to better performance (both time taken as well as error rate) than no fit.

**DISCUSSION AND IMPLICATIONS**

**Discussion of Findings**

An important contribution of this study is the empirical demonstration of how to assess mental representations through the proposal and validation of two competing problem solving processes. While the importance of mental representation has been discussed, prior research has focused on validating the cognitive fit theory by only measuring the performance effects of cognitive fit (Shaft & Vessey, 2006). There has been little research targeted towards providing a better understanding of what mental representation constitutes and how it can be estimated and verified in a research setting.

In order to perform the task using the A1 and the R1C1 problem representations, users

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**Figure 6. Distribution of precedent cells for big-cell spreadsheet**

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have to expend significant cognitive effort as the task is a visual spatial task while the problem representations are not. Users have to transform information from the problem representation to form the mental representations—A1-anchored and dependent-anchored for A1 and R1C1 representations respectively. The experimental data supports H1 and H2 (which were developed based on Hick’s law), thus providing empirical validation to our reasoning regarding the formation of mental representations.

We theoretically explain the notion of alternative fit and the laboratory experiment is designed to examine this alternative fit. Hypotheses 3 and 4 are supported by the experimental data showing that an alternative fit occurs for A1 representation, but does not occur for R1C1 representation.

The experimental findings (Figure 7 to Figure 10) further indicate that for both representations, performance is better in big-cell spreadsheets than in default cell spreadsheets. Hick’s law explains the better timing for big-cell spreadsheets, since there are fewer cells to choose from. This finding may also be partially explained by Fitts’ law (Fitts, 1954) which models human movement in human-computer interactions and predicts that the times required in moving to a target is a function of the distance to and the size of the target, and moving the

**Table 1. Performance results: means and standard deviations (in parentheses)**

<table>
<thead>
<tr>
<th>Problem Representation</th>
<th>Time (milliseconds)</th>
<th>Error rate (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Default-cell spreadsheet</td>
<td>Big-cell spreadsheet</td>
</tr>
<tr>
<td>A1</td>
<td>5,196 (1,056)</td>
<td>2,646 (355)</td>
</tr>
<tr>
<td>R1C1</td>
<td>11,199 (3450)</td>
<td>4,262 (860)</td>
</tr>
</tbody>
</table>

Figure 7. Time-distance plot for default-size spreadsheet
mouse to the identified precedent cell is a part of the task. However, Fitt’s law can only be used to estimate mouse movement time and not the decision-making time (Thimbleby, 2004) and does not also explain the occurrence of fewer errors for big-cell spreadsheets.

**Implications for Research and Practice**

A primary contribution of this paper is the development of alternative fit between the problem representation and the mental representation, which provides insights for re-examining prior...
studies using cognitive fit theory. For example, the question of whether a tabular presentation or a graphical presentation is better has been studied through manipulating the original fit between task and problem representation, in the context of different tasks to fit a table or a graph (Vessey & Galletta, 1991); and by adding interactive “value” tags to graphs to create a problem representation that is both graphical and textual (Kumar & Benbasat 2004). Our study indicates that it will be worthwhile to consider the alternative fit in such studies, for example, by studying how different components of the graph result in the creation of mental models which in turn may or may not fit with other parts of the graph. The extended theory enables analysis from a different perspective. This extended theory can also be tested in other areas.

Problem solving takes place through the mental representation by mentally transforming information. Since mental transformation takes time and effort, it affects task performance (Vessey, 2006). Drawing from the model theoretic approach towards cognitive problem solving which uses the notion of mental models to explain cognitive task performance, we explain the creation of different mental representations for different problem representations. It is desirable to have a good fit between the created mental representation and the (other parts of the) problem representation for improved performance.

A recent study of the cognitive fit model distinguishes between external problem representation (the representation of the problem that users are provided with) and internal problem representation (a representation of the problem domain that exists in the user’s mind), and states that interactions between the internal and external problem representations, and task representation contribute towards the creation of the mental representation for task performance (Vessey, 2006; Khatri, Vessey, Ram, & Ramesh, 2006; Chandra & Krovi, 1999). Our
study extends this idea by showing that even without considering the influence of task, it is possible to assess mental representation by only considering the problem representation and how it influences mental representation. Therefore, while task is an integral aspect of research aimed towards assessing the design, usability and effectiveness of information technology tools and applications (Zhang & Eseryel, 2005), this research proposes an alternative mechanism of assessing the effectiveness of information technology tools.

Understanding decision-making strategies is an important aspect of HCI research (Fern et al., 2010) as it can help in designing more effective interfaces. Previous research has shown that cognitive modeling techniques are helpful as decision support tools for organizational decision-making (Kwahk, Kim, & Chan, 2007). This study therefore has important practical implications that can be applied to the spreadsheet context. While spreadsheets are widely used in organizations, spreadsheet errors are relatively common and often result in serious consequences (Chan, 2004; Panko, 2008; Panko & Halverson, 1996; 2001). Spreadsheet comprehension is a key to several spreadsheet related tasks such as updating spreadsheets, auditing spreadsheets or spreadsheet error correction. Therefore, it is of practical importance to understand the factors that influence spreadsheet comprehension. By selecting a task that is crucial to understanding the structure of a spreadsheet – that of finding precedent cells – this study shows the effect of different spreadsheet referencing styles on task performance. Although past research has advocated the use of visualization tools to support chaining (Chan, 2004; Davis, 1996; Goswami et al., 2008; Hendry & Green, 1993; Sajaniemi, 2000), this research shows that chaining performance can be also influenced simply by using different spreadsheet referencing styles. Future research can investigate the effect of different

Figure 10. Error-distance plot for big-cell spreadsheet

![Error-distance plot for big-cell spreadsheet](image)
referencing styles on higher level spreadsheet tasks such as error correction, detection, and updating spreadsheet. Such research can help in the selection of a referencing technique that is suitable for the task being performed.

For tracing cell precedents, this study finds that the R1C1 referencing style is not as effective as the A1 referencing style. Developers can consider redesigning the R1C1 style. For instance, columns and rows can be dynamically renumbered from the dependent cell in order to fit the problem solving process that is anchored to the dependent cell. Developers can also examine other possible problem representations that give a better match with the task of finding precedents. Future studies on spreadsheet analysis can test other problem representations for the same task of finding precedents, or other spreadsheet analysis tasks.

It is important to realize that the concept of alternative fit may be generalized to other applications. For example, a more general practical implication is that a problem representation should avoid inconsistent parts that may lead to the creation of multiple mental models for a single task. The R1C1 style is an example of a problem representation with inconsistent parts. An example from a different domain is a problem that presents liquid volumes in imperial units (e.g., pints and gallons) and liquid containers in metric units (e.g., liters and milliliters), where the inconsistent representations will likely result in a misfit. The implication for users and decision makers will be to aim for a consistent problem representation. For interactive systems, the effort for consistent problem representation may need the conscious effort of designers and developers.

Limitations

The results of this study should be interpreted in the context of its limitations. The use of a controlled laboratory experiment gives rise to limitations inherent to experiments. The use of student subjects is a practical limitation; even so, prior research has argued that this does not necessarily affect the generalizability of the results (Campbell, 1986; Dipboye & Flanagan, 1979) and the results of this study may be generalizable to other populations with good general training or education. Another concern may be the existence of a learning effect, as reflected by the performance improvement observed in the data between round 1 and 2. Performance may improve further over time. In the experiment, results are consistent over two rounds; however there is no certainty that they will remain the same if the subjects had continued for many more rounds. The experiment was designed to be a simple one involving only one precedent cell for a dependent cell. Further, the experiment and the formulas were designed in such a way that both the dependent and the precedent cell could be viewed in the same screen without subjects having to scroll through the spreadsheet either horizontally or vertically. Simplicity is needed for experiments in order to minimize possible confounds. However, the hypotheses developed can be tested for generalizability to other areas.

The performance difference between problem presentations may also be partly caused by factors other than fit. This is an inherent difficulty in studies using the cognitive fit theory. It is almost impossible to constrain the problem representations to differ only in terms of fit; it is also usually not desirable to do so (Chandra & Krovi, 1999). In this experiment, some may argue that the “A1” referencing style has higher readability compared to the “R1C1” referencing style. The experiment tried to control for the readability effect by keeping the formula very simple: it has only one precedent cell with no other mathematical operations. Also, reading difficulty will be a constant effect, and not dependent on the location of the precedent cell, and thus would not contradict the timing equations found in the experiment.

This study assumed the starting points of users’ search process for the two problem representations, in order to derive the number of choices and predict the time needed for task performance. While the regression results and the high R² values for the regression models support this assumption, using a process tracing
technique such as by capturing cursor movements and recording users’ eye movement might shed more light on the actual problem solving process and strengthen our reasoning behind the two mental representations.

CONCLUSION

Going beyond previous research, this study analyses mental representation, proposing two competing problem solving processes, which in turn were identified empirically using Hick’s law – an established law for predicting response time. The experiment in this study provides empirical support to identify the mental representation used by subjects. This approach of proposing and validating the mental representations increases the internal validity of the cognitive fit study. This study also outlines an alternative fit between problem representation and mental representation, and thus provides a new extension to the cognitive fit theory. This fit is different from the original fit between task and problem representation. This study further shows how one component of a problem representation can influence mental representation, how this mental representation can fit with other components of the problem representation and affect task performance. The theoretical finding provides practical implications not only for spreadsheet designers, but also for other users and designers dealing with or specifying problem representations.

REFERENCES


**ENDNOTES**

1. This is done for convenience, Using a different logarithm base results in a different constant, and does not affect the regression significance.

2. MANOVA analysis shows the same significant findings.

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