

## Chapter 4

### HYPOTHESES

Because one of the purposes of this study is to replicate the experiment conducted by C&H, the first nine hypotheses are the same as those that appeared in the original study.

#### 4.1 C&H HYPOTHESES:

- H1:** Subjects who receive behavior modeling training will develop higher perceptions of computer self-efficacy than subjects who receive non-modeling training.
- H2:** Subjects who receive behavior modeling training will develop higher outcome expectations than subjects who receive non-modeling training.
- H3:** Subjects who receive behavior modeling training will score higher than those in non-modeling training on measures of performance.
- H4:** Individuals with high computer self-efficacy will demonstrate higher outcome expectations regarding computer use than individuals with low self-efficacy.
- H5:** Individuals with high computer self-efficacy will score higher than those with low computer self-efficacy on measures of performance.
- H6:** Individuals who expect positive outcomes from their use of computers will exhibit higher performance than those who do not expect positive outcomes.

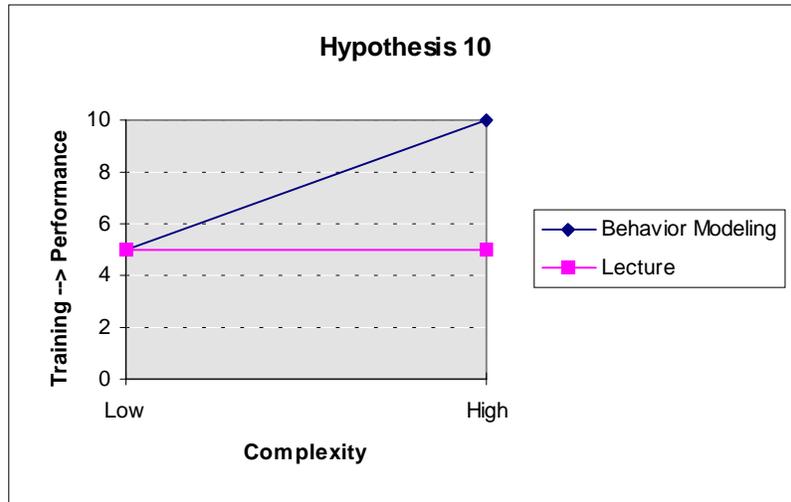
- H7:** Subjects with higher prior computer performance scores will develop higher perceptions of computer self-efficacy than subjects with lower prior performance scores.
- H8:** Subjects with higher prior computer performance scores will develop higher outcome expectations than subjects with lower prior performance scores.
- H9:** Subjects with higher prior performance scores will exhibit higher performance than subjects with lower prior performance scores. (Compeau and Higgins, 1995)

C&H found little or no support for Hypotheses 2, 6, and 8, which involve outcome expectations. They reasoned that because performance is a short-term measure, while outcome expectations involve a long-term perspective, a comparison of the two variables is not possible in a single test of performance. Although their reasoning appears rational in light of their findings, Bandura (1977, 1978) argues that outcome expectations do affect performance and are, in turn, affected by prior performance, behavior modeling, and self-efficacy. This paper again hypothesizes and tests these relationships to determine if the original "null" findings were mere artifacts of the data or actual "null" effects.

#### **4.2 TASK COMPLEXITY HYPOTHESES:**

The next set of hypotheses addresses the effect of the moderating variable, task complexity. Given the results of the C&H study, in which behavior modeling had a greater positive effect on performance than lecture based training in Lotus tasks (high complexity) but had no incremental improvement for performance in Word Perfect tasks (low complexity), the following hypothesis is derived:

- H10:** Behavior modeling will have a greater positive effect on performance than traditional lecture based training when task complexity is high.



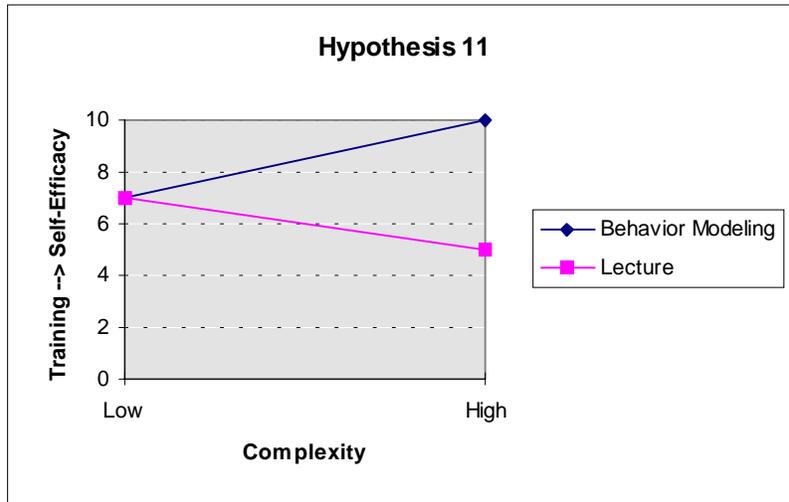
**Figure 4.1 Hypothesis 10: Chart of Predicted Interaction**

The figure above illustrates the expected interaction between the effects of types of training on performance and levels of complexity. When task complexity is high, Behavior modeling is expected to exhibit a higher influence on performance than that caused by lecture-based training.

One should note that Hypothesis-10 does not address the effects of behavior modeling or lecture-based training at the low level of task complexity. In the original C&H study, behavior modeling was not found to be *more* effective for performance in any of the word processing sessions. Therefore, it can only be assumed that the two training methods are at least statistically equivalent at low levels of complexity. This predicted ordinal interaction is illustrated in Figure 4.1.

C&H found a significant positive effect for behavior modeling on computer self-efficacy for both Lotus sessions. For the WordPerfect training, however, they found that behavior modeling did not significantly enhance self-efficacy for Day 1 of the instruction. Moreover, the significant **negative** effect that was observed on Day 2 of the word processing training is interpreted as subjects who received behavior modeling training actually developed **lower** self-efficacy than subjects in the lecture-based training group. Given these unexpected results, the next hypothesis is derived:

**H11:** Behavior modeling will have a greater positive effect on computer self-efficacy than traditional lecture-based training when task complexity is high.



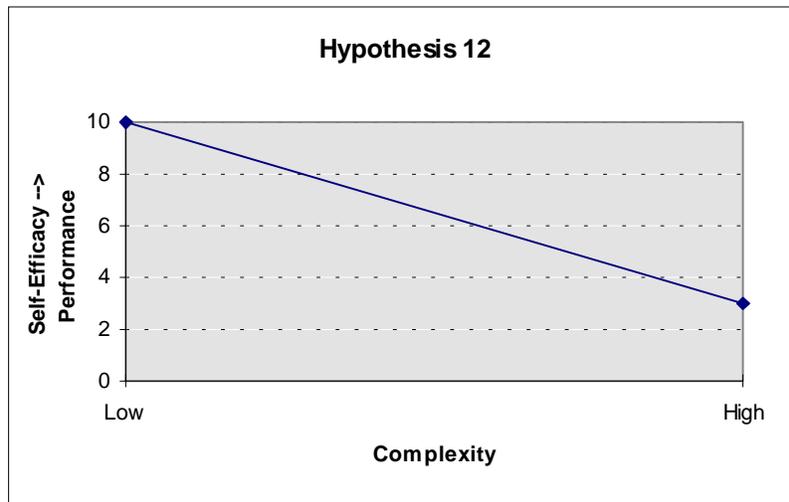
**Figure 4.2 Hypothesis 11: Chart of Predicted Interaction**

The figure above illustrates the expected interaction between the effects of types of training on self-efficacy and task complexity. Behavior modeling is hypothesized to have a greater effect on self-efficacy than lecture-based training when task complexity is high.

It is expected, given the results of the C&H study, that the high level of complexity will produce a significant difference between training methods for measures of self-efficacy. This ordinal interaction is illustrated in Figure 4.2.

As previously stated, Gist and Mitchell (1992) suggest that the "predictive validity of self-efficacy for performance on complex tasks may be weaker than for performance on simple tasks." The following hypothesis states this relationship in testable form and is illustrated in Figure 4.3.

**H12:** Self-efficacy will have a greater positive effect on performance for both behavior modeling and traditional lecture-based training when task complexity is low than when task complexity is high.



**Figure 4.3 Hypothesis 12: Chart of Predicted Interaction**

The figure above illustrates the expected results of the effects of self-efficacy on performance and task complexity. At low levels of complexity, the effect of self-efficacy on performance is expected to be higher than at the high level of complexity.

All of the hypotheses listed above will be tested using structural equation modeling. In order to test the moderating effects of task complexity, separate models must be evaluated. Some of these models were initially presented in the path diagrams in Chapter 1. Greater detail regarding the method of analysis for these models is presented in Chapter 6.

### **4.3 MISCELLANEOUS HYPOTHESES: AVOIDANCE BEHAVIOR**

In the historical Social Cognitive Model, Bandura (1977) proposed that vicarious experience could be used to enhance self-efficacy and, in turn, reduce avoidance behavior. He defined avoidance behavior as the active or passive resistance of activities deemed as fearful, stressful, or otherwise ineffective. Bandura asserted that by increasing a person's self-efficacy using vicarious experience and, thereby, reducing performance anxiety, that person would be less likely to avoid situations in which failure could result.

In the context of this study, Task Avoidance is the resistance to use the technology

provided to perform a given task. Following Bandura's reasoning, individuals who are given behavior modeling training and vicariously experience feelings of success will have higher levels of self-efficacy and fewer instances of avoidance behavior than individuals receiving non-modeling training. Thus, behavior modeling individuals will exhibit avoidance behavior (i.e. choose **not** to use the technology provided) less often than non-modeling subjects.

**H13:** Subjects who receive behavior modeling training will elect to use the given technology more frequently than subjects in the non-modeling group.

In addition to the overall effect of behavior modeling on the decision to use the technology provided, task complexity may play a vital role. Davis (1989) suggests that people adjust their decision-making strategies and, ultimately, their decisions to use computers, based on their perceptions of task complexity.

In this study, two opposing factors may influence users' decisions to use the technology. Sanders and Courtney (1985), in their analysis of DSS success, assert that as the "user's task environment becomes more chaotic, decision aids may burden the decision maker." It follows then, at high levels of complexity, subjects will attempt to perform their tasks without the added burden of understanding and using a new technology.

On the other hand, cognitive mapping also may affect the decision to use the technology at low levels of complexity. Bostrom, Olfman, and Sien (1990) argue that a person's mental model, an internal representation of his/her understanding of a specific task or system, governs attitudes and the decision to use systems.

In this study, subjects initially may possess mental models of the low complexity task. Because the low complexity task can be solved without using the technology provided, it is believed that most subjects will inherently want to solve the low complexity task using their existing mental models without using the technology. Fortunately, mental

models are not permanent and can be altered through a process of training: “Learning is viewed as a process of model transformation, i.e. a progression through increasingly sophisticated mental models where each reflects a more adequate understanding of the target software.”<sup>1</sup> (Bostrom et al, 1990)

Assuming that training will eliminate cognitive mapping artifacts at the low level of complexity, it is hypothesized that subjects who exhibit avoidance behavior will do so at the high level of task complexity due to the added burden of understanding not only the task, but also the technology provided.

**H14:** Avoidance behavior will be exhibited more frequently at the high level of task complexity than at the low level of task complexity. That is, of those subjects who do **not** elect to use the technology, more will do so at the high level of complexity than at the low level of complexity.

A summary of all hypotheses is presented in Table 4.1.

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<sup>1</sup> Bostrom et al. (1990) identify three methodologies that are used to alter mental models, or cognitive maps: (1) Mapping via usage, (2) Mapping via analogy, and (3) Mapping via training. Within the third methodology, Mapping via training, *Applications-based training* is a technique that is task-oriented and often is used to form task-centered mental models. More precisely, by specifically training subjects on the use of the technology provided to perform low complexity tasks, the ability to use the technology should transcend subjects’ existing cognitive maps. Thus, training is expected to overcome any confounds related to cognitive mapping.

**Table 4.1 Summary of Hypotheses**

<b>C&amp;H Hypotheses</b>	
<b>H1:</b>	Training --> Self-Efficacy (Behavior Modeling > Lecture)
<b>H2:</b>	Training --> Outcome Expectations (Behavior Modeling > Lecture)
<b>H3:</b>	Training --> Performance (Behavior Modeling > Lecture)
<b>H4:</b>	Self-Efficacy --> Outcome Expectations
<b>H5:</b>	Self-Efficacy --> Performance
<b>H6:</b>	Outcome Expectations --> Performance
<b>H7:</b>	Prior Performance --> Self-Efficacy
<b>H8:</b>	Prior Performance --> Outcome Expectations
<b>H9:</b>	Prior Performance --> Performance
<b>Task Complexity Hypotheses</b>	
<b>H10:</b>	Training --> Performance (moderated by complexity)
<b>H11:</b>	Training --> Self-Efficacy (moderated by complexity)
<b>H12:</b>	Self-Efficacy --> Performance (moderated by complexity)
<b>Avoidance Behavior Hypotheses</b>	
<b>H13:</b>	More subjects will use the technology (Behavior Modeling > Lecture)
<b>H14:</b>	More subjects will use the technology (Low Complexity > High Complexity)

#### **4.4 RECONCILIATION OF C&H TO GSR**

As stated previously, Compeau and Higgins (1995) based much of their study on an experiment conducted by Gist, Schwoerer, and Rosen (1989). It may be recalled that C&H compared behavior modeling to a non-modeling technique, lecture-based training, whereas GSR compared behavior modeling to a different non-modeling technique,

computer-aided instruction (CAI). In both studies, behavior modeling was found to be superior to the non-modeling approaches. What was not addressed, however, was a comparison between the two non-modeling approaches.

Traditional lecture-based training plus hands-on experience is the “dominant form of formal training in North American organizations.” (Compeau & Higgins, 1995) Computer-aided instruction, on the other-hand, is an affordable, self-paced approach that gradually is becoming more popular because users and organizations are experiencing increased time and budgetary constraints. Unlike behavior modeling and lecture-based training, CAI requires active participation from the user as these applications are usually on-line tutorials that include programmed instruction, exercises, and feedback (Gist et al., 1989).

To date, no known research has attempted to classify or rank non-modeling training methods in terms of effectiveness. Consequently, little is known about the effectiveness of computer-aided tutorials in relation to lecture-based training. Intuitively, CAI techniques demand active participation from users, whereas lecture-based training methods require only passive involvement. Although it is possible for users to “tune out” any instructional method, it seems less likely that users will do so in the CAI sessions. Conversely, lecture-based training provides two sensory stimuli (auditory and visual) whereas CAI provides only one (visual). Wickens (1992) states that maximal learning occurs when users are given redundant auditory and visual displays of instructions. Thus, using this reasoning, it seems likely that lecture-based training will outperform CAI training.

Whether the effect of active participation will surpass the effect of multiple sensory stimuli is an empirical question that is left to speculation. Given that two opposing forces may be operating on performance in the non-modeling sessions, no formal hypotheses are presented to address the directionality or existence of differences between the effects of lecture-based and CAI training methods on final performance. Also, because no theory

exists to corroborate the possibility of differences in self-efficacy or outcome expectations across non-modeling conditions, comparison of lecture-based training to computer-aided instruction is purely exploratory.