Learning Cognitive Feedback Specificity during Training and the Effect on Learning for Cognitive Tasks

A dissertation presented to
the faculty of
the College of Arts and Sciences of Ohio University

In partial fulfillment
of the requirements for the degree
Doctor of Philosophy

Ryan J. Yoder

November 2009

© 2009 Ryan J. Yoder. All Rights Reserved.
This dissertation titled
Learning Cognitive Feedback Specificity during Training and the Effect on Learning for
Cognitive Tasks

by

RYAN J. YODER

has been approved for
the Department of Psychology
and the College of Arts and Sciences by

__________________________
Jeffrey B. Vancouver
Professor of Psychology

__________________________
Benjamin M. Ogles
Dean, College of Arts and Sciences
Abstract

YODER, RYAN J., Ph.D., November 2009, Psychology

Learning Cognitive Feedback Specificity during Training and the Effect on Learning for Cognitive Tasks (144 pp.)

Director of Dissertation: Jeffrey B. Vancouver

Providing advice to improving training interventions is a high priority among applied psychology researchers. One element of training that is under the control of providers is the nature of feedback provided to learners. Higher specificity of the feedback message has generally been considered beneficial for performance and learning. However, recent research has qualified this relationship, suggesting that the specificity of feedback leads to different types of learning. Less specific feedback encourages task exploration and learning how to respond when task conditions are unfavorable, but is detrimental to learning how to respond when task conditions are favorable. To date, only the specificity of cognitive (i.e., task-related) feedback has been explored. In this study, learning cognitive (i.e., learning-related) feedback was manipulated. This feedback represented feedback about how well one implements abstract learning principles aimed at systematically exploring the task environment. After training, learning on a later transfer task and generalization task (where rules governing task performance had changed) was measured. It was predicted that high learning cognitive feedback specificity would reinforce learning strategies and aid individuals in the generalization transfer task beyond task-related feedback messages. Those participants receiving high specificity learning cognitive feedback showed better learning on a generalization transfer task than
individuals receiving low specificity learning cognitive feedback. The results of this study have implications for designing feedback interventions that maximize distal learning outcomes. Specifically, feedback designed to support learning principles can positively affect performance for task conditions not specifically trained for.

Approved: _____________________________________________________________

Jeffrey B. Vancouver

Professor of Psychology
Dedication

To my parents for giving me the opportunity to pursue scholastic achievement and for their continued love and support in everything I do.

To my son for his patience in letting daddy write when he should have been playing. I love you Reid.

And to my wife Kristina, for her love and support and for always believing the end was in sight.
Acknowledgments

I would like to begin by acknowledging several individuals whose help and support made the completion of this dissertation possible. First, I would like to thank my committee chair, Jeff Vancouver, for his direction and assistance invested in this project. His dedication to quality scholarly work has made this dissertation a better project and paper. I would also like to thank Paula Popovich, Rodger Griffeth, George Johanson, and Amy Taylor-Bianco for their time and effort serving on my committee. Their insights and tough questions improved the quality of this paper.
# Table of Contents

<table>
<thead>
<tr>
<th>Section</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abstract</td>
<td>3</td>
</tr>
<tr>
<td>Dedication</td>
<td>5</td>
</tr>
<tr>
<td>Acknowledgments</td>
<td>6</td>
</tr>
<tr>
<td>List of Tables</td>
<td>10</td>
</tr>
<tr>
<td>List of Figures</td>
<td>11</td>
</tr>
<tr>
<td>Introduction</td>
<td>12</td>
</tr>
<tr>
<td>Historic Treatment of the External Feedback Specificity and Learning Relationship</td>
<td>14</td>
</tr>
<tr>
<td>Knowledge of results</td>
<td>16</td>
</tr>
<tr>
<td>Cognitive feedback</td>
<td>21</td>
</tr>
<tr>
<td>Summary</td>
<td>27</td>
</tr>
<tr>
<td>Emergent Issues in the External Feedback Specificity and Learning Relationship</td>
<td>30</td>
</tr>
<tr>
<td>Guidance hypothesis</td>
<td>33</td>
</tr>
<tr>
<td>Guided guidance hypothesis</td>
<td>46</td>
</tr>
<tr>
<td>The Current Study</td>
<td>53</td>
</tr>
<tr>
<td>Method</td>
<td>59</td>
</tr>
<tr>
<td>Overview</td>
<td>59</td>
</tr>
<tr>
<td>Participants</td>
<td>60</td>
</tr>
</tbody>
</table>
List of Tables

Table 1. Participant Decisions for the Furniture Factory Employees ................................ 69
Table 2. Decision Rules: Set A .......................................................................................... 71
Table 3. Decision Rules Set B ........................................................................................... 73
Table 4. Correlations Among Variables ............................................................................ 90
Table 5. Repeated Measures Analysis of Variance: The Effects of Feedback Specificities on Performances ................................................................................................................ 93
# List of Figures

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 1. Framework for Cognitive Feedback</td>
<td>24</td>
<td></td>
</tr>
<tr>
<td>Figure 2. Tower of Hanoi Puzzle</td>
<td>38</td>
<td></td>
</tr>
<tr>
<td>Figure 3. Assigning Employees to Production Jobs</td>
<td>66</td>
<td></td>
</tr>
<tr>
<td>Figure 4. Assigning Levels of the Motivating Variables to Employees</td>
<td>67</td>
<td></td>
</tr>
<tr>
<td>Figure 5. Low-Task Feedback Specificity Example</td>
<td>74</td>
<td></td>
</tr>
<tr>
<td>Figure 6. High-learning Feedback Specificity, Screen Shot 1</td>
<td>76</td>
<td></td>
</tr>
<tr>
<td>Figure 7. High-learning Feedback Specificity, Screen Shot 2</td>
<td>78</td>
<td></td>
</tr>
<tr>
<td>Figure 8. High-Task Feedback Specificity Example</td>
<td>79</td>
<td></td>
</tr>
<tr>
<td>Figure 9. Feedback Specificity Performance Across Trials</td>
<td>91</td>
<td></td>
</tr>
<tr>
<td>Figure 10. Feedback Specificity Conditions and Good vs. Poor Performance Rule Learning</td>
<td>96</td>
<td></td>
</tr>
<tr>
<td>Figure 11. Learning Feedback Specificity Performance During Far Transfer</td>
<td>99</td>
<td></td>
</tr>
</tbody>
</table>
Introduction

Change and development are a reality of organizational life. Today, many organizations strategically plan and prepare for changes by training and developing the members of the organization to be good learners on the job and in the business environment (Cascio & Aguinis, 2005). Training refers to the acquisition of knowledge, skills, and attitudes for immediate or near-term use (Kraiger, 2003). It is the systematic acquisition of skills, rules, concepts, or attitudes that result in improved performance in another environment (Goldstein & Ford, 2002). For the training to have long-term benefit for the organization, it must produce learning that has long-term retention and positive transfer to an anticipated posttraining environment (Bjork, 1994). Training researchers have long studied learning principles that foster these positive outcomes.

One principle almost universally used is providing trainees with feedback during training (Cascio & Aguinis, 2005; Goldstein & Ford, 2002). Providing individuals with feedback has been one of the most widely studied and applied psychological interventions in the history of psychology (Ilgen, Fisher, & Taylor, 1979; Kluger & DeNisi, 1996, 1998). In the training literature, this type of feedback is commonly viewed as “actions taken by an external agent(s) to provide information regarding some aspects(s) of one’s task performance” (Kluger & DeNisi, 1996, p. 255). In the organizational literature, feedback is seen as important for the learning, motivation, and performance of individuals (Fedor & Buckley, 1987). Prescriptions for the implementation of feedback into training programs abound. For example, it is generally believed that frequent, immediate, and specific feedback (i.e., feedback provided by a
coworker or supervisor) is beneficial to the aforementioned outcomes (Bernardin & Beatty, 1984; Campbell & Kuncel, 2002; Kolb, Rubin, & McIntyre, 1980; Kreitner, 1977). These recommendations have direct implications for practitioners. In particular, the ubiquitous belief that highly specific, or detailed, feedback translates into more positive outcomes can be seen in the prescriptions made for practitioners developing feedback interventions in the training (e.g., Goldstein & Ford, 2002) and coaching and development (e.g., Kreitner & Kinicki, 2001) literatures.

However, some researchers have called into question the prescription to provide specific feedback in training (Bjork, 1994; Christina & Bjork, 1991; Salmoni, Schmidt, & Walter, 1984; Schmidt & Bjork, 1992; Schmidt, Young, Swinnen, & Shapiro, 1989), particularly for complex cognitive tasks (Goodman & Wood, 2004; Goodman, Wood, & Hendrickx, 2004). These researchers note that much of the previous research has neglected to examine differences in learning (via task performance) over time. In these studies, trainee learning has been assessed during the training session and the transfer of learning to the performance environment (i.e., back on the job) has been largely ignored (Bjork, 1994; Christina & Bjork, 1991, Salmoni, et al., 1984; Schmidt & Bjork, 1992). Research beginning to examine transfer or long term effects suggests that the positive results associated with specific feedback may not be realized over time, and may even become detrimental to future performance (Goodman, et al., 2004; Goodman & Wood, 2004). Although this emerging literature has begun to specify the mechanisms through which a negative relationship occurs, it has only focused on the provision of one type of specific feedback, namely feedback about the task environment. Just as previous research
can be criticized for failing to investigate learning outcomes over time, current research can be criticized for its narrow definition of specific feedback. In particular, this literature has neglected to examine how task information feedback could be responsible for creating the negative relationship between feedback specificity and learning outcomes.

The purpose of the current study is to examine feedback specificity and its effects on learning outcomes in a posttraining environment. To this end, I begin with a discussion of feedback specificity and its relationship with performance and learning. Then, I discuss construct validity regarding task learning measures and the effects this research has had on understanding the nature of feedback specificity. In particular, I focus on the guidance hypothesis (Schmidt et al., 1989) and how it currently shapes the understanding of the specificity relationship for cognitively complex tasks. Finally, I discuss questions unanswered by the newer research, and conclude by proposing a study that will utilize a paradigm favored in the feedback specificity literature.

**Historic Treatment of the External Feedback Specificity and Learning Relationship**

The concept of feedback is broad in scope. According to Ilgen, et al. (1979) feedback can be thought of as a special case of general communication where information is conveyed to a recipient about his or her performance. According to Doherty and Balzer (1988), feedback can be thought of as the process by which an environment returns to individuals a portion of the information from their actions in the environment, such that he or she can compare a present strategy with a representation of an ideal strategy. Feedback can be received from several sources. The most often studied source of feedback in the training literature has been external feedback. External
feedback can be reduced to two sources, primary and secondary. Both types of external feedback present information about the past behavior of an individual (Annett, 1969).

Primary external feedback is often described as task-generated, resulting from task engagement. It occurs naturally within the task environment, such that the individual can observe it without the need of an external agent. When performing certain tasks, feedback about one’s performance in the task becomes immediately apparent. For example, if an individual were participating in a pursuit tracking task where the individual was asked to point a laser toward a moving target, the individual would receive immediate feedback about performance as he or she observed the relative position of the laser beam to the target he or she was trying to follow. Primary external feedback is also called response-produced feedback and is the direct result or consequence of task engagement (Adams, 1971; Annett, 1969).

Primary external feedback includes, among other things, observable changes in the task across trials; conditions indicating progress from task execution; and other output characteristics such as speed, quality, and condition as they relate to goal achievement. During task execution, performers can generate feedback by comparing what has been done or is being done to the process or outcome requirements of the task. That is, sensory information (i.e., sight, touch, hearing, smell, and/or taste) may result as a function of task execution and can indicate the effects of what the performer has done (Christina & Bjork, 1991). Required task processes and outcomes (i.e., referent data) can come from a variety of sources. Referent data could include instructions for performing the task correctly or could come from task expectations of the performer, as well as other sources.
As the task is executed, discrepancies or errors can be detected by the performer as they compare sensory information to referent data. If the effects of executed behaviors do not bring about change, such that discrepancies or errors are not reduced, then the performer may adjust future behaviors to bring about desired change.

Secondary external feedback has generated the most research in the training literature. It is typically provided by an individual or entity that has observed the behavior of the feedback recipient and is in a position to evaluate said behavior. This feedback involves some level of information about one’s task performance (Kluger & DeNisi, 1996). The observer forms perceptions about the recipient’s performance to develop a feedback message that can inform the performer regarding how well he or she is performing on the task. Throughout the feedback literature, secondary external feedback has most often taken the form of information about the effectiveness of one’s actions, such as “you made 80% of your free-throw shots.” This type of feedback, generally referred to as outcome, knowledge of performance, or knowledge of results (KR) feedback (Balzer, Doherty, O’Conner, 1989), is about the response outcome (in terms of task goals) rather than about a given response (Salmoni, et al., 1984). In this dissertation I adopt the label knowledge of results to refer to this type of feedback. Below I review the literature on knowledge of results.

_Knowledge of results._ Many researchers have held an underlying assumption that knowledge of results (KR) feedback consistently improves learning and performance (Kluger & DeNisi, 1996). The assumption stems from some of the earliest work done in the area of motor task learning by Thorndike (1913; 1927). In particular, Thorndike’s law
of effect described that secondary external feedback has both positive effects (via reinforcement) and negative effects (via punishment) that, when taken together, direct or improve performance when an individual is learning how to respond to a stimulus. When an individual responds to a stimulus and engages in the correct behavior, secondary external feedback can provide reinforcement by encouraging the individual to engage in effective behavior in the future when the stimulus occurs again. Similarly, when the individual responds incorrectly to a stimulus, secondary external feedback can provide punishment to the individual such that they will be less likely to engage in the incorrect behavior in the future when the stimulus is again present (Thorndike, 1913; 1927). Moreover, Thorndike theorized that KR facilitated learning by strengthening the stimulus-response connection (through reinforcement), which should improve performance.

Thorndike’s theories laid the groundwork for not only the effects of KR on learning and performance, but also the necessity of such feedback for learning. During this time learning was often assessed as performance on the trained task. Many of the early researchers interpreted their studies as support for the positive effects of KR on learning and performance (e.g., Arps, 1920; Book & Norvell, 1922; Brown, 1932; Gilliland, 1925; Johanason, 1922; Manzer, 1935; Pressy, 1950; Smith, 1933; Spencer, 1923; Waters, 1933). By the late 1930s, a sizeable number of studies had been conducted showing that KR was an important variable. According to the findings up to this point, KR would lead to improvement in performance. Additionally, little improvement could occur without KR and, when it was withdrawn, performance tended to deteriorate. For
example, two empirical pieces cited as evidence of the effectiveness of KR for learning include work by Bilodeau, Bilodeau, and Schumsky (1959) and Trowbridge and Cason (1932). These studies demonstrated that when participants were not given outcome feedback (KR), they were unable to reduce errors in performance on motor tasks. They were unable to learn the correct movements needed to yield the correct motor response in each of the two tasks. In the first study, participants were asked to draw lines of a certain length and were given feedback about achieving the desired length, typical of several of Thorndike’s early studies. The other study involved moving levers to their appropriate positions with or without KR feedback.

An early and popular review of the feedback literature by Ammons (1956) drew several conclusions from the literature that further solidified the positive relationship in the scientific community. One conclusion he drew was that KR increases learning. Specifically, he noted that KR accelerates the rate at which learning occurs and the level of learning achieved (Ammons, 1956). Ammons used a study by Pressy (1950) to substantiate his conclusion. In Pressy’s study, participants were given immediate self-scoring devices to help them learn English vocabulary. Participants were either given the self-scoring device or not (i.e., given outcome feedback or no feedback). He found that providing KR improved learning. Additionally, Ammons cited a study by Book and Norvell (1922), where participants were given KR that improved learning. However, Kluger and DeNisi (1996; 1998) criticize Ammons’ review, as he was somewhat selective in his use of the available research used to justify his conclusions. For example, Ammons neglected Pressy’s finding that KR decreased learning of Russian vocabulary
compared to no feedback. Additionally, Ammons failed to mention that in the Book and Norvell study, most of the participants (better than 75%) in the control conditions also increased in learning performance.

Later reviews by Adams (1978), Annett (1969), Bilodeau (1969a, 1969b), and Irion (1969) all highlighted the shortcomings of the law of effect when examining available research. For example, Annett (1969) re-evaluated the motor, perceptual skills, and verbal learning literatures and noted that there is more to KR than its reinforcement effect (i.e., rewarding correct and punishing incorrect responses) proposed by Thorndike.

Balanced against motivational effects are the informational effects of feedback. Feedback provides informational value to the recipient that reduces the uncertainty or ambiguity about his or her performance (Annett, 1969). The effect of these various forces on task performance and learning can become complicated depending on the nature of the task for which the KR feedback is given. Annett argued that it is potentially impossible to dissect the contribution of these individual influences for explaining the result of KR feedback on learning and performance. Indeed, Annett felt that KR may or may not present a boost to recipient performance in the short term on some tasks, and effects may or may not last in the longer term on others.

In their review of the early feedback intervention research, Kluger and DeNisi (1996) noted that many of the historic KR feedback studies suffered from poor or inaccurate operationalizations of KR, faulty methodology, and lack of attention given to results inconsistent with theorizing. Given these problems, the authors argue that few conclusions could be drawn. At best, a cursory look at the state of the literature would
lead one to conclude that the relationship is anything but straightforward, contrary to the suggestions of Thorndike’s theories (Annett, 1969; Kluger & DeNisi, 1996). At times it was suggested that the presence of KR feedback enhanced task learning and performance above controls (e.g., Arps, 1920; Gilliland, 1925; Johanason, 1922; Thorndike, 1927; Waters, 1933; Wright, 1906). Additionally, increased frequency with which KR was provided during training often led to enhanced learning and performance over decreased frequency. Yet, at other times KR feedback had no or a negative relationship with learning and performance (e.g., Deputy, 1929; Locke, 1967; Locke & Bryan, 1969; Spencer, 1923). Indeed, in their meta-analysis Kluger and DeNisi (1996) provided a summary and state of the literature for the effects of feedback interventions (external feedback) on performance. They found that providing feedback positively improved task performance ($d = .40$) over providing no feedback. The authors argued that the literature has often ignored the large amount of variability in the effectiveness of secondary external feedback. Indeed, they also found that secondary external feedback actually reduced performance in about one third of the cases they investigated.

The Kluger and DeNisi (1996) meta-analysis provided a sense of the diversity of the findings in the feedback literature, but did not investigate the relationship between secondary external feedback and learning per se. However, a meta-analysis by Harris and Rosenthal (1985) did indirectly examine the relationship. In their study, they examined the effect of teachers’ expectations on students’ classroom performance (i.e., learning assessed via performance on achievement tests) and found that feedback was positively, but very weakly, related to performance ($r = 0.07$). In fact, it was the least effective
mediator, following a) having contact with the student $(r = 0.20)$, b) setting challenging goals $(r = 0.33)$, and c) creating a better environment $(r = 0.37)$. Similarly, Callahan, Kiker, and Cross (2003) conducted a meta-analysis examining the effectiveness of various instructional factors on training performance for older learners. They found a non-significant negative relationship between the presence of KR and training performance.

Taken together, reviews and meta-analyses investigating the relationship between KR feedback and learning/performance imply that the relationship is often positive, but it is not straightforward as to how positive or when the relationship might change. It may depend on the nature of the feedback given and the type of task being trained. The evolution of this literature implies that the type of feedback given will differentially affect the results of different types of training tasks. That is, it may be the case that what might work well for motor tasks may not be as effective with cognitive learning tasks. In the next section, we see that researchers propose that more informative secondary external feedback can enhance the positive relationship, particularly when cognitive tasks are being trained.

Cognitive feedback. To this point, much of the feedback literature examining the relationship between secondary external feedback and learning only considered feedback messages about overall performance (KR). Researchers began looking beyond KR feedback that only indicates how well individuals were performing, to providing feedback that informed the learner about how to improve task performance. This type of secondary external feedback includes information about how to perform an action, such
as “your hand should follow through behind the ball as you take your free-throw shot.” This more detailed and specific information describing critiques about how to perform an action is often referred to as process or cognitive feedback (Balzer, et al., 1989; Salmoni, et al., 1984). It can include information about physical movements or the correctness of decisions made that improved or detracted task performance, depending on the type of task being trained (i.e., a motor or cognitive task).

Much of the previous literature had focused on motor learning tasks using KR to assess the effectiveness of secondary external feedback. Although KR feedback had often been found to be positively related to performance for motor learning tasks, some began to argue that this might not hold true for many cognitive learning tasks (predominately during the 1970s and 1980s). They argued that individuals are often unable to infer complex environmental relationships on their own without some type of external feedback (e.g., Balzer et al., 1989). Often individuals lack insight into their own judgment and decision-making strategies, such that they do not know how to go about discovering environmental relationships (Balke, Hammond, & Meyer, 1973; Brehmer, 1980). Additionally, outcome feedback alone is not sufficient to allow individuals to divine such relationships (Balzer et al., 1989).

Research using cognitive feedback demonstrates that KR provided during training is often detrimental to training performance on complex cognitive tasks involving dynamic decision making (Balzer et al., 1989). KR impedes performance by encouraging participants to haphazardly experiment with multiple decision strategies. Providing KR feedback stimulates the recipient to test new strategies as to how to perform the task in
more efficient ways. However, this action decreases judgment consistency in the task and confounds the participants’ testing of hypotheses, which, it has been hypothesized, will lead to lower levels of learning and subsequent performance (Balzer et al., 1989). Individuals are unable to utilize KR effectively to learn appropriate response behavior in uncertain environments. Several studies have found that outcome feedback alone can, at best, have no effect on short-term learning or can deter learning on complex and dynamic cognitive tasks for individuals (Brehmer, 1980; Hammond, Stewart, Brehmer, & Steinmann, 1975; Hammond & Summers, 1972; Hammond, Summers, & Deane, 1973; Lepper & Gurtner, 1989; Schmitt, Coyle, & Saari, 1977; Wise, Plake, Pozehl, Barnes, & Lukin, 1989). Many of these studies represented the nonconforming findings that Kluger and DeNisi (1996) discussed in their meta-analysis. These researchers find that to enhance task performance and learning, trainees should instead be given cognitive or process feedback (Todd & Hammond, 1965) about their performance that details how their judgments can be improved toward congruence with task demands.

Cognitive feedback refers to information about the relations between variables rather than performance outcomes (Balzer et al., 1989). A common paradigm used to examine cognitive feedback is called multiple-cue probability learning (MCPL). This research relies on a version of the Brunswik (1956) lens model, re-formulated by Hammond, Hursch, and Todd (1964). In this model, cognitive feedback recipients can be given, potentially, three different types of information corresponding to the three different components of the decision-making environment (Balzer et al., 1989). Specifically, recipients can receive information “about relations in the environment,
relations perceived by the person, and relations between the environment and the person’s perceptions” (Balzer et al., 1989, p.410). Figure 1 illustrates the relationship between the environment and subject with respect to the three types of cognitive feedback; task information, cognitive information, and functional validity information.

![Diagram](attachment:Framework_for_Cognitive_Feedback.png)

**Figure 1.** Framework for Cognitive Feedback

In a complex decision-making task there are underlying rules governing the dynamics of the environment. Different decisions made bring about different outcomes in the environment. These outcomes may also be contingent on environmental cues that also

---

change; decisions may be differentially effective depending on the nature of the current
state of the environment. Feedback about these rules and their dynamics is commonly
referred to as task information (Balzer et al., 1989). Task information is information
about the relationship between environmental cues (Xs) and the criterion (Ye),
information about the criterion itself (i.e., how it is defined), information about
environmental cues (i.e., how cues are related and can be used to understand the
underlying processes), or all three (Balzer et al., 1989). In the cognitive feedback
literature task information has been the most often studied and has been consistently
found the most impactful on participant learning and performance (Balzer et al., 1989).

The participant employs various decisions to learn the underlying rules of their
environment. They will employ these decisions in either some systematic or haphazard
way, such that they are able to learn or fail to learn relationships between decisions and
outcomes. During this process the participant creates their own hypotheses about the
nature of the rules underlying task dynamics and tests these hypotheses accordingly.
Cognitive feedback about the relationship between participant decision-making and each
environmental cue represents cognitive information (Balzer et al., 1989). It is information
about the recipient’s own judgment system. Often this type of cognitive feedback attunes
the participant to the consistency with which he or she applies decisions in the task
environment given individual cues (Balzer et al., 1989).

Lastly, the recipient can receive cognitive feedback called functional validity
information (Balzer, et al., 1989). According to Balzer et al. (1989), this type of
information can refer to the relationship between the recipient’s judgments on the task
and the nature of the environment (i.e., the correctness of his or her judgments), the relationship between the linear models of the recipient and environment (i.e., knowledge of the correct linear prediction of the judgments), and the relationship between the residuals resulting from the prediction of those linear models (i.e., knowledge of the correct nonlinearity in the prediction of the judgments if nonlinearity exists). All of above types of cognitive feedback (i.e., task information, cognitive information, and functional validity information) represent different types of process information that can be given to recipients; or they can be selectively given depending on the nature of the task.

Additionally, cognitive feedback can be given orally by an instructor, or can be given graphically/pictorially through computer aided instruction (Balzer et al., 1989). This type of feedback enables recipients to enhance performance and learning by providing insights into properties of the task environment, the nature of the recipient’s judgment policies, and the correspondence between both (Balzer et al., 1989).

Azevedo and Bernard (1995) meta-analytically reviewed the use of cognitive feedback in computer-based instruction. In the studies reviewed, all feedback was cognitive and provided through adaptive computer systems to participant learners. Additionally, studies included in their meta-analysis were divided based on the time of their assessment of learning. Fourteen studies examined learning effects directly after training (i.e., immediate posttest). In these studies a positive relationship was found for the cognitive feedback-learning relationship with an overall weighted mean effect size of 0.80. Similarly, three studies examined learning effects some time after training occurred (i.e., delayed posttest). Although the relationship remained positive, the overall weighted
mean effect size dropped to 0.35. The authors argued that the drop in the effect size for the cognitive feedback-learning relationship over time was an artifact of a manipulation employed in the studies examining longer-term retention (Azevedo & Bernard, 1995). Specifically, these studies examined delays in the presentation of feedback to participant learners. They believed that had these studies provided cognitive feedback immediately after performance the effect size from these three studies would have been larger (Azevedo & Bernard, 1995).

Taken together, this literature implies that for complex cognitive tasks, one should present feedback to the learner that is appropriately cognitive. Presenting cognitive feedback promotes feedback messages that are inherently more specific than KR or outcome feedback. Indeed, the specificity of the feedback message refers to the level of detail of information presented in the message (Annett, 1969). Most of the aforementioned studies have traditionally implemented (and imply one should implement) cognitive feedback by providing individuals with either more detailed feedback about the correctness of their judgments and decisions or instructions about how they should have performed given the task circumstances. Often, both of these messages provide information about a decision rule set specified and known by the experimenter, but not the trainee. The cognitive feedback literature is clear that the net effects of cognitive feedback about task information on learning how to perform various tasks is positive.

Summary. The secondary external feedback literature has a long history that arguably began with the work of Thorndike. Although his theorizing generated much
empirical work on the topic, reviewers have noted that much of this work was seriously flawed, and few conclusions could be drawn from it other than the notion that the relationship of feedback with learning and performance is anything but straightforward (Kluger & DeNisi, 1996). Looking at the literature at a more detailed level seemed to reveal more interpretable findings. In the case of motor task learning, it is often found that when KR is provided, it enhances task learning and subsequent performance above controls with whom no KR is given (Kluger & DeNissi, 1996). Additionally, the more frequent KR is given during motor task learning (e.g., KR presented every trial versus every five trials), the stronger the effect on learning and performance (Kluger & DeNissi, 1996).

The findings are different when examining more cognitively complex tasks. For these types of tasks, KR does not provide individuals with enough information to infer complex environmental relationships (Balzer et al., 1989). Instead, KR encourages the recipient to experiment with multiple decision strategies that can decrease decision consistency and confound decision-making (Balzer et al., 1989). For cognitively complex tasks, the findings show that cognitive feedback is more likely to improve training performance (i.e., learning) when compared to controls (Balzer et al., 1989). Cognitive feedback presents a higher level of detail and specificity of information presented in the feedback message than outcome (KR) feedback. It provides recipients with information about the errors that they make; allowing them to take corrective action. Alerting recipients of their errors appears to help them identify which of their behaviors are effective and which are ineffective for successful performance (Adams, 1987; Anderson,
1982; Annett, 1969; Ilgen et al., 1979; Payne & Hauty, 1955). With increasing levels of specificity of information in the feedback message, recipients receive greater detail about corrective information for their previous behavior. This, in turn, helps them further recognize the source of their errors and facilitates subsequent adjustments leading to enhanced learning and performance on the task (Annett, 1969; Baron, 1988; Goldstein, Emanuel, & Howell, 1968; Payne & Hauty, 1955). According to a review by Kopelman (1986), feedback high in specificity tells performers how to reach criterion levels sooner; leading to enhanced performance over less specific feedback.

However, at the time many researchers were studying the effects of cognitive feedback for enhancing learning from training, others were beginning to rethink the construct validity of learning measures. Whereas the above results appear to be robust and useful to organizations, some have raised the possibility that much of the previous work did not do a good job at examining long-term learning and transfer (Christina & Bjork, 1991; Schmidt & Bjork, 1992). Up to this point, learning was most often measured immediately following training or during the training itself. Today, few, if any, researchers would contend that differences among individuals, in terms of training performance, can be assumed to translate into similar differences in posttraining or transfer performance. Indeed, what is most important to many researchers and organizational trainers alike is the effect that training has on posttraining performance (e.g., performance back on the job).

Several studies have made the case that training performance may or may not be a good predictor of posttraining performance, even when both performance contexts are
very similar (Christina & Bjork, 1991). These critics note there are reasons for not assuming that greater short-term learning is a prerequisite or important first step for distal outcomes like long-term learning and transfer. They contend that many of the best practices traditionally advocated in the training literature (i.e., those that enhance performance during training described above) might actually be detrimental to performance in the posttraining environment (Schmidt & Bjork, 1992). I examine these arguments and the literature this group has generated next.

**Emergent Issues in the External Feedback Specificity and Learning Relationship**

Two major factors are indicative of training transfer to the posttraining or performance environment; the similarity between training and posttraining tasks and the level of original learning occurring from training (Christina & Bjork, 1991). Gick and Holyoak (1987) note that any salient similarities between the training and posttraining (i.e., transfer) tasks will influence the trainee’s perceived similarity between the tasks. In turn, this will elicit the trainee to retrieve mental representations of the training situation, which are previously developed, and apply them to the transfer task. Christina and Bjork (1991) argue that when the perceived similarity is high, it is more likely that the trainee will attempt to transfer what was learned during training to the posttraining task. Thus, the training tasks should approximate the performance tasks to enhance the effectiveness of the transfer of the training.

In addition to trainee perception, the level of original learning from training is a major determinant of the level of retention and subsequent transfer of the learner to later tasks. Of this there is little disagreement. However, measuring original learning directly
following training (via practice or training performance) is a potentially confounded variable. Indeed, Christina and Bjork (1991) and Salmoni et al. (1984) argue that learning, as assessed during training, likely includes both true learning effects and transient learning effects. True learning effects are those that we are interested in assessing because they are the ones that will last over time and are relatively permanent (Christina & Bjork, 1991). They represent actual acquisition of skills, understanding, and knowledge gained from the training. Also, they will last even though changes will undoubtedly occur between training and posttraining performance contexts.

Alternatively, transient learning effects do not last over time (Christina & Bjork, 1991). They represent either ephemeral changes in the individual or effects that only occur in the presence of certain contextual variables, which are conditions of the training/practice environment not present in the posttraining environment (Christina & Bjork). These latter effects are artificial learning effects in that they are supported by particular environmental conditions of the training, but when these conditions change, or are not present, the apparent learning effects supported by the environmental conditions disappear. For example, providing trainees with secondary external feedback (e.g., KR or cognitive) represents a condition of the training which may not be present in the posttraining environment, and will differentially influence the measurement of learning during training and posttraining. Today, several have argued (e.g., Christina & Bjork, 1991; Salmoni et al. 1984; Schmidt & Bjork 1992; Schmidt, et al., 1989) that because we are most interested in assessing learning as transfer to the posttraining environment, we should measure learning as represented by performance across time in the posttraining
environment or in a real-world setting that is the target of the training. Doing so provides a more accurate measure of original learning through eliminating the transient artifacts of the training environment (Christina & Bjork, 1991; Schmidt & Bjork, 1992).

Armed with a new perspective in the construct validity of learning measures, researchers began to re-examine the effectiveness of secondary external feedback toward fostering learning. Conventional thinking about the function of many traditional learning concepts has been investigated with this concern in mind. In a review of some of this new work, Schmidt and Bjork (1992) provided findings from both motor and cognitive task learning studies and used them to suggest that many common assumptions about training and practice are not supported when learning is assessed over time. In particular, Schmidt and Bjork reported that feedback frequency (with respect to motor task learning) and feedback specificity (with respect to cognitive task learning) effect training performance and posttraining, or retention performance, differentially. Indeed, KR feedback given less frequently impairs practice performance relative to frequently given feedback, although transfer performance is enhanced over time (Schmidt, et al., 1989; Winston & Schmidt, 1990; Wulf & Schmidt, 1989).

Similarly, cognitive feedback, high in specificity, has also been found to be related to enhanced short-term performance for both motor and cognitive tasks. However, when learning is assessed at a later time, for cognitive tasks, the amount of feedback specificity is negatively related to learning performance, such that those taught with high specificity under-perform relative to those taught with low specificity (Goodman & Wood, 2007; Goodman & Wood, 2004; Goodman, et al., 2004). In both the motor and
cognitive task learning areas, researchers have cited the \textit{guidance hypothesis} as the rationale for the reversal in these new findings with the new learning measures. The guidance hypothesis states that secondary external feedback can be both beneficial to short-term performance, while impairing long-term learning (Bjork, 1994; Christina & Bjork, 1991; Schmidt & Bjork, 1992). Indeed, it is often found that factors that deter performance during training (e.g., lack of specificity in the feedback message), or that make short-term performance more difficult, tend to lead to better retention and enhanced performance on posttraining tasks (Bjork, 1994; Christina & Bjork, 1991; Schmidt & Bjork, 1992). The logic of the guidance hypothesis is described next.

\textit{Guidance hypothesis.} The essence of the guidance hypothesis is that secondary external feedback high in specificity provides a strong guidance function for future performance (Salmoni, et al., 1984, Schmidt, et al., 1989). Specifically, feedback provided during training guides learners to correct responses, leading to enhanced practice or training performance. Yet, the guidance resulting from this feedback decreases the amount of active information processing that learners might otherwise engage in if the feedback were not present (Goodman, 1998; Goodman & Wood, 2004). For example, say one was teaching someone to play the game chess. To that end, the instructor could provide various levels of feedback specificity after having taught the mechanics of the game. A high feedback specificity approach might be watching the individual play and telling him or her moves to make in order to win. A low feedback specificity approach might take the form of watching him or her play without providing any feedback from the instructor. However, the individual would still receive outcome
feedback from the game. With respect to performance during the training, the student given high feedback specificity would no doubt perform better. Indeed, the low feedback specificity student, left to make his or her own decisions and mistakes, would likely make decision errors and lose. However, if asked to play the game in the future, the guidance hypothesis would predict that the student trained under low feedback specificity would outperform the high feedback specificity trained student because of the active information processing that the latter student engaged in during training that the former student was not required to engage in because the “answers” were freely given. That is, the latter student actually “learned” how to play the game of chess.

According to early theorizing, not only was secondary external feedback an important learning variable, but that without it, no learning can occur at all (Thorndike, 1913; 1927). This is particularly true when primary external feedback is not available to the learner. However, Annett (1969) later proposed that, for many tasks, primary external feedback is really all that is necessary for learning, when it is available. Salmoni et al., (1984) described that secondary external feedback can become diminished in its importance on task learning when primary, response-produced feedback is redundant with secondary external feedback. That is, the effectiveness of the feedback for learning can in part be determined by the extent to which it overlaps feedback naturally occurring in the task environment. However, for tasks where primary external feedback is available to the participant; the learner is less likely to pay attention to it if secondary external feedback is also available. Additionally, this distraction effect is most pervasive when the feedback is highly specific in its message (Goodman & et al., 2004, Schmidt & Bjork,
This leads learners to rely on the secondary external feedback. However, if such feedback is not present after training (i.e., the post-training or transfer environment), performance suffers (Schmidt & Bjork, 1992).

For most tasks, particularly those that are cognitively complex, learning how to perform the task well in response to changing task conditions requires both actively searching the task for information, and processing found information to develop an understanding between actions and outcomes in the task (Klahr & Dunbar, 1988; Simon & Lea, 1974). Secondary external feedback about performance on the task provides individuals with some of this information about the effectiveness of their actions. It allows them to experiment and test alternative responses in order to understand these relationships through monitoring changes in performance. Yet, as the task becomes more complex, the amount of exploration and information processing required to discover the underlying relationships or the decision rules for the task also increases (Klahr & Dunbar, 1988). When highly specific secondary external feedback is given, it enhances the corrective function of the feedback for future behavior leading to a reduction in the amount of decision errors made and enhanced short-term performance (Goodman & et al., 2004, Schmidt & Bjork, 1992). However, highly specific secondary external feedback also requires less systematic exploration and information processing activities on the part of the recipient because action-response relationships are detailed in the feedback message (Schmidt, 1991). Task exploration is reduced because the specific feedback directs the recipient to make multiple decision changes at the same time without seeing the effects of individual changes on properties of the task environment over time (i.e.,
decision-making is confounded). This enhances immediate task performance while also making feedback recipients less inclined to derive action-outcome relationships on their own (Schmidt, 1991). Instead, recipients come to rely on the specific secondary external feedback for guidance in task decisions, and, as a result, they are also less likely to remember their previous responses (Christina & Bjork, 1991; Schmidt, 1991; Schmidt & Bjork, 1992).

In contrast, when less specific feedback is available individuals must rely on their own abilities in navigating the task environment. Because recipients are not given correct decision responses through the feedback message, they will be prone to make decision errors and will need to derive meaning from those errors with respect to engaging in the task environment (Schmidt, 1991; Schmidt & Bjork, 1992). That is, they must engage in more task exploration and more information processing of their errors than their high feedback specificity counterparts. Although this hinders short-term performance, making decision errors actually serves several useful functions. These errors help develop one’s mental model of the task, which is useful for developing new insights into the task (Frese, Brodbeck, Heinbokel, Mooser, Schleiffenbaum, & Thiemann, 1991). Also, they create opportunities to learn how to engage the task when performance on the task is poor (Goodman et al., 2004). Not only does the guidance, resulting from reliance on the specific feedback encourage the recipient to engage in less information processing activities (i.e., how should I approach the problem of learning how to perform this task), but the recipient also has fewer opportunities to experience making decision errors and determine what he or she should do in response to wrong decisions (i.e., when an error
occurs, what should be my next step towards correcting the error) when learning how to
perform a task. It is predicted that this, in turn, decreases the extent to which the recipient
can learn how to correct decision errors and enhance performance when performing the
task at a later time when the secondary external feedback is removed.

Within the guidance hypothesis framework it is believed that learning really
occurs on trials where no secondary external feedback is provided or on trials with low
feedback specificity (Salmoni et al., 1984). Particularly, long-term retention and learning
will occur through the processing of primary external feedback that can be recalled in
posttraining contexts. Primary external feedback is believed to be necessary for the
development of error detection and correction skills required for learning (Salmoni et al.,
1984). Thus, learning will primarily occur from searching for information in the task
space, processing information coming from the task environment, encoding, and
retrieving identified action-outcome linkages.

In sum, the guidance hypothesis states that although feedback high in specificity
will help recipients more quickly discern behaviors appropriate for successful
performance in the short-term, it also encourages recipients to become cognitively lazy.
The result is a decrease in the information-processing activities of the feedback recipient
needed for performance in the long-term (Christina & Bjork, 1991). Instead, recipients
require the secondary external feedback to perform the task in a later posttraining context.

Several studies have begun to investigate the validity of the guidance hypothesis
in cognitive task learning. A study by Goodman (1998) examined and found some
support for the hypothesis using a computer-based version of the Tower of Hanoi puzzle
(Simon, 1975; Anzai & Simon, 1979). The Tower of Hanoi puzzle consists of three pegs on a board, which are labeled Peg A, Peg B, and Peg C from left to right (Figure 2). There are four objects of different sizes stacked on Peg A in order of size from the largest on the bottom to the smallest on the top. The goal is to discover the optimal method for transferring those objects to Peg C following these rules: a) only one object may be moved at a time, b) no larger object may be placed on a smaller object, c) no object may be moved that has another object lying on top of it. The optimal method for the four-tier puzzle requires 15 moves.

![Figure 2. Tower of Hanoi Puzzle](image)

In this study, Goodman examined primary external feedback that included 1) observable changes in the task across trials; 2) conditions indicating progress from task execution; and 3) other output characteristics such as speed, quality, and condition as they related to goal achievement. It was put to participants to learn how to solve the
puzzle given the parameters of their condition. In this experiment, the amount of secondary external feedback provided was manipulated. Secondary external feedback was given either continuously or not at all, and came in the form of both cognitive and KR feedback. Recipients of secondary external feedback were told the number of moves that they had made in the game so far and the number of moves they should have made so far. The differences between these two numbers represented the number of errors that had been made so far. Additionally, a message from the computer was given after each move, indicating whether or not the recipient had made the correct move. When the move was incorrect, the recipient was provided with the correct move.

The amount of primary external feedback in the task was also manipulated. In the low primary external feedback condition, participants did not move the objects in the puzzle. Instead, they designated where the pieces would be moved to, and the puzzle pieces remained in their original position on the first peg. This way they were not able to visually compare the different sizes of the pieces through moving them on the computer screen. In the high primary external feedback condition, participants were able to move pieces that could be moved, according to the rules, around on the computer screen to compare their relative sizes. This allowed them to plan which moves they would like to make in accordance with puzzle rules. Also, it gave participants the ability to visually monitor task progress toward task goals.

Learning was measured via participant performance on the task at a testing, or transfer, phase (seven days later), where no secondary external feedback was provided to any of the participants. Goodman (1998) found that the presence of secondary external
feedback improved practice performance levels in the amount of correct moves required to complete the task, the time it took to complete the task, and the incidence of the first error made in the task. Additionally, when no secondary external feedback was given, those in the high primary external feedback condition outperformed those in the low primary external feedback condition. However, these differences disappeared when secondary external feedback was given. With respect to learning, Goodman found that those who received secondary external feedback during practice took longer to perform the task and made their first error earlier during later testing. Additionally, those given primary external feedback completed the task in fewer moves, less time, and made their first error later in the task. Finally, the effect of primary external feedback on learning was partially mediated by error detection and correction when performing the task during testing. This study was one of the first studies to demonstrate that the presence of secondary external feedback, although enhancing practice performance, could negatively impact later performances.

Not only were the researchers interested in demonstrating the performance and learning effects resulting from feedback guidance, but also the effect of feedback specificity on exploration activities in task decision-making. A more recent study by Goodman et al. (2004) used the Furniture Factory simulation to examine the effect of secondary external feedback specificity on learning through systematic and unsystematic exploration of the task space. The Furniture Factory (Wood & Bailey, 1985) is a computer simulation designed to explore differences between external feedback specificity and learning relationships given different types of external feedback.
Specifically, participants served as managers over several employees and were given weekly furniture orders to fill. Each “week” participants assign each employee to a job in order to fill the order and then also assign levels of goals, feedback, and rewards to each employee to motivate them to perform their job better. After these decisions are made, an algorithm, unknown to the participant, applies the decision rules of the simulation to the participant’s decisions to determine individual employee and work team performance for meeting the weekly order.

In the Goodman et al. (2008) version of the game, participants were given low, moderate, high, or very high specificity secondary external feedback about their managerial decisions. In the low specificity condition, participants received KR feedback including weekly job performance levels for individual employees and the entire factory. In addition to the feedback given in the low specificity condition, those receiving moderate specificity feedback were also given error signal (i.e., cognitive) feedback about their decisions. They were informed if they had made all of their decisions correctly or not. In addition to the feedback given in the moderate specificity condition, those receiving high or very high specificity feedback were also given more error signal (i.e., more cognitive) feedback about their decisions. They were informed if they had made decisions about individual employees correctly or not. As previously mentioned, an underlying performance algorithm governed employee performance and the algorithm required different courses of action depending on the performance of the employee.

Learning was assessed later at a testing period (two days later) in two ways. First, participants were again asked to be managers in the Furniture Factory using the same
performance algorithm used in the training phase. Then, they were instructed to play again only this time their workers began the simulation with low performance levels, meaning that all participants were forced to be exposed to the ineffective worker-side of the performance algorithm. During testing, no secondary external feedback was given to any of the participants. Additionally, systematic and unsystematic exploration was assessed by examining if the participant made decisions in a manner consistent with the logic of hypothesis testing within an unconfounded experimental design (Tschirgi, 1980; Vollmeyer, Burns, & Holyoak, 1996). That is, changing just one factor for a worker each trial and assessing the result on worker performance. During the practice phase of the experiment, participants could engage in systematic or unsystematic exploration zero to three times per trial for a total of 48 times.

The results of the Goodman et al. (2008) study found that high specificity feedback was associated with enhanced participant performance during the practice phase. As expected, they found that feedback specificity was negatively related to both systematic and unsystematic exploration in task decision-making. Guidance resulting from the high specificity feedback discouraged any task exploration activities, be they systematic and useful for learning or unsystematic and haphazard. In turn, these researchers confirmed that systematic exploration was positively related to task learning, as assessed during the testing phase, and unsystematic exploration was negatively related. Yet, inconsistent with theorizing, they failed to find support for a main effect (i.e., a negative relationship between feedback specificity and task learning). They did, however, find that participants in the low and moderate specificity conditions performed the best
during the testing phase trials. Later, Goodman and Wood (2004) argued that the reason a main effect was not found in this study was because overall measures of learning obscured external feedback specificity effects. This is, because feedback differentially effects participant learning of correct responses to good versus poor task performance. Meaning the algorithm describing the relationship between decisions made and their effects on performance are different when performance in the task is good and when it is poor. Because specific feedback accelerates good performance in the task, the feedback recipient is less likely to learn how to perform under poor task performance circumstances. Thus, the negative effect on learning is most pronounced for learning the poor performance aspect of the decision algorithm.

The last study examining the feedback specificity-learning relationship comes from Goodman and Wood (2004). In this follow-up study, participants again played the Furniture Factory computer simulation (Wood et al., 1990). Like the study by Goodman et al. (2004), this study included a manipulation of secondary external feedback specificity. Again, learning was assessed at a later transfer phase as described above. Goodman and Wood (2004) found that secondary external feedback specificity affected good and poor worker performance algorithm learning differentially, as expected. This indicated that participants given higher specificity feedback made their decisions correctly, and as a consequence, were unable to learn how to handle workers with poorer performance levels, which was the focus of the later training phase simulation. Specifically, they found that when it came to good performance rule learning, those given high feedback specificity did better in transfer. When it came to poor performance rule
learning, those given low feedback specificity did better. The authors argued that this left participants given higher specificity feedback with a disadvantage at the testing phase such that they were unable to learn how to increase poor worker performance during that task. Those administered less specific feedback during the practice phase had the opportunity to develop strategies for exploring the task space in order to enhance worker performance when initial worker performance was poor during later testing. Thus, those who received feedback of varying specificities learned different things, through different means. High feedback specificity encouraged better good performance rule learning while low feedback specificity encouraged better poor performance rule learning. Goodman and Wood argued that the feedback specificity question is more complex than high versus low, but depends upon what kind of learning trainers want trainees to take away from training.

Each of these studies lend some support to the notion that specific secondary external feedback, while positive for practice performance, can differentially affect long-term task performance learning. In these studies (i.e., Goodman et al., 2004; Goodman & Wood, 2004), participants given highly specific secondary external feedback perform well in the task and, as a result, do not get experience with all aspects of the worker performance algorithm during training. It should not be surprising that when participants are given the opportunity to engage the simulation several days later, and the workers under-perform relative to training, that those not exposed to the poor worker performance aspect of the algorithm, perform poorly relative to those experiencing poor performers. It is also worth noting that the specific, secondary external feedback provided in these
studies (i.e., the cognitive feedback) is always information about the correctness of the decisions made by the participants for their workers (i.e., task information).

In summary, past research might be misleading regarding the effects of secondary external feedback beyond immediate training because until recently studies have not incorporated transfer tasks in experimental designs (Salmoni, et al., 1984). According to Schmidt and Bjork (1991), there is likely a learning component in measures of practice performance, but these measures are unclear about the amount learned because they can confound true learning effects with more transient effects induced as a result of the training context. To date, secondary external feedback specificity and its relationship to learning (via task performance on post-training transfer tasks) has only begun to be examined with respect to cognitive task learning (e.g., Goodman & Wood, 2004; Goodman et al., 2004; Goodman & Wood, 2007). Findings lend evidence that increased secondary external feedback specificity, although generally improving performance during practice, is differentially related to subsequent transfer task performance (i.e., task learning), measured days after the initial training session.

Yet, there are some questions about the robustness of the secondary external feedback specificity relationship to learning outcomes on cognitive tasks. Specifically, these studies have investigated specificity through cognitive feedback relegated to task information, or relationships between environmental cues and the underlying rules governing the task performance. However, it is often the case that during training, we would want to teach trainees how to learn to engage the task environment in order to divine such relationships for themselves. This is particularly true when the dynamics of
the posttraining task are unknown during training. In this case, we might ask participants to learn how to maximally perform. Task information promotes the trainee to learn the known rule set, but does not effectively teach the trainee how they should attempt to divine an unknown rule set in an ambiguous or uncertain context. Conversely, knowledge of results feedback seems to foster greater information processing (i.e., more systematic exploration than cognitive feedback) towards divining such rules on cognitively complex tasks, yet still take much time to train and develop learning skills. It seems that a marriage of these two types of feedback could result in the provision of a specific feedback message that encourages systematic task exploration in a more timely fashion.

In the next section, I describe what this marriage could look like.

**Guided guidance hypothesis.** Instead of giving trainees cognitive feedback about task information, we might opt for feedback that is more epistemic or helpful for developing the ability to learn for oneself. This type of learning cognitive feedback, could direct participants toward understanding their own decision-making processes instead of rote information about the environment. This feedback would reference how well the participants were conforming to the systematic observation of the task environment. That is, instead of giving only KR, or giving cognitive task-feedback about what decisions should be made in the training task, we could give feedback that would support and reinforce general learning principles during training. This would enable the learner to utilize the skills learned from training to a different future cognitive (i.e., decision-making) task. For example, we could train an individual how to engage in systematic decision-making. Rather than give cognitive task-based feedback, we could provide the
trainee with specific feedback about how well he or she is engaging in systematic exploration and not making confounded decisions. The feedback we provide would not tell him or her how to improve in the current task, *per se*, but rather how to learn about engaging in good decision-making practices when confronted with ambiguous decisions. This more epistemic feedback is also of the specific variety (i.e., cognitive feedback), but it involves feedback about learning principles and how those principles are evoked in situations of uncertainty, with respect to the kinds of tasks one might find in the performance environment. This way, trainees would have better awareness about how they are engaging in cognitively complex tasks and if they were acting in accordance with learning principles.

For example, to determine which course of action should be taken in a changing environment, the individual may have to employ multiple decisions over time in order to understand action-response connections in the environment. When faced with this type of complex problem, and a dynamic environment, there are several types of exploration activities in which an individual can engage. However, these exploration activities are not equally effective for discovering underlying decision rules linking actions to outcomes (Debowski, Wood, & Bandura, 2001). For instance, in response to feedback, an individual could continually make the same decisions over and over again, or they could vary different decisions based on feedback. Consistently making the same decisions over each presentation of the problem would not bring much new information to the participant. He or she could also employ multiple decisions at once, or could employ only one decision at a time and attend to how it changes the variable of interest over time. By
making multiple decision changes at the same time, the effect of an individual change is confounded. This unsystematic exploration technique would not provide the individual with useful information for discerning the underlying relationships. However, the former strategy of decision-making would yield the most information. Specifically, by systematically changing one thing at a time, the individual can avoid confounded information in the feedback message, such that he or she could identify the effects of various decisions on other properties of the task (Tschirgi, 1980).

An empirical question is whether the change in the nature of the secondary external feedback provided (i.e., change from feedback about task information to feedback about learning) would produce the same results that are currently discussed in the cognitive task learning literature (i.e., differential relationship between specificity and learning during transfer). That is, the learning cognitive feedback would be highly specific in terms of the feedback message, yet it seems unlikely that this feedback would have adverse learning effects. Indeed, if we give specific feedback about how well one is utilizing systematic learning strategies, then we might expect that those given a more detailed feedback message would more readily learn how to learn about a task environment. This would, in turn, lead to enhanced performance during a posttraining, transfer phase, task where the dynamics of the task change from the initial training task.

Several areas of research within the training literature provide some support for an epistemic feedback strategy. In the area of training content (i.e., the type of material that should be covered in training), it has long been recognized that greater posttraining transfer, and learning, can be achieved by teaching trainees general, rather than specific,
principles about a given topic (Baldwin & Ford, 1988). That is, when trainees are taught, not just applicable skills, but also general rules and theoretical principles underlying the training content, then greater transfer and learning can be achieved (McGehee & Thayer, 1961). For example, early research in this area, conducted by Judd (1908) and Hendrickson and Schroeder (1941), illustrate training participants how to shoot underwater targets. Participant’s taught general principles were also instructed about the properties of light infraction on the surface of water. When the depth of the targets in the water changed during training, it was found that those given the more general instruction were able to adapt to different shooting environments and performed better than those simply taught to shoot at an underwater target. Similarly, a study by Goldbeck, Bernstein, Hillix, and Marx (1957) demonstrated that individuals instructed in general principles for a common problem-solving technique were better able to locate problems with malfunctioning electronic equipment than those not taught the general principle.

Providing learning cognitive feedback that supports and reinforces general learning principles should bolster learning transfer to a future environment better than task-information feedback.

A second, emerging line of research within the training literature examines the effects of adaptive guidance, or active learning approaches, on learning. Adaptive guidance is a self-regulatory approach to training effectiveness where the instructional strategy is designed to assist trainees towards making effective learning decisions through the provision of diagnostic and interpretive information (Bell & Kozlowski, 2002; Bell & Kozlowski, 2008; Smith, Ford, & Kozlowski, 1997). That is, adaptive guidance provides
trainees with information regarding past performance (i.e., typically KR feedback) and helps them interpret it to determine appropriate future directions to take. For example, a student learning the piano could be told that they correctly “played” 60% of his or her notes during a practice performance. Additionally, he or she could be told that his or her posture was subpar for most of the piece; therefore, he or she should work to improve posture over the next practice piece in an effort to play more notes accurately.

In a study by Bell and Kozlowski (2002), adaptive guidance (i.e., cognitive feedback about task information) was compared to knowledge of results feedback for learning a radar-tracking computer simulation. They collected a single wave of data employing a complex cognitive task. Their study included a posttraining generalization task that was the same as the training task except it had enhanced complexity (the properties of the task did not change, but there was more to monitor in the task environment than during training). Like Goodman and Wood (2004), Bell and Kozlowski (2002) found that adaptive guidance (i.e., high specificity feedback) enhanced training performance. However, unlike Goodman and Wood’s study, they found that adaptive guidance led to enhanced performance in the generalization task (performed directly following training).

There are two important distinctions that can be made between the Bell and Kozlowski study and the Goodman and Wood study. First, the dynamic natures of the two tasks employed in these studies are different. While both tasks are dynamic in nature, the underlying rules governing performance in the Bell and Kozlowski study are not dynamic. That is, in the Bell and Kozlowski study, the correctness of a given decision is
not dependent on the correctness of past decisions. In the Goodman and Wood study, past participant performance determines the correctness of future courses of action. Secondly, the nature of the cognitive feedback provided in the Bell and Kozlowski study is different than the cognitive feedback provided in the Goodman and Wood study. The former study used feedback that was more instructional than typical process feedback. It went beyond telling correct or incorrect decisions made and instead provided information about how to interpret feedback and steps to improve performance. Thus, this study provides evidence that instructional feedback can be beneficial to generalization in a posttraining task, as I am hypothesizing.

However, adaptive guidance diverges from learning cognitive feedback in that the former directs trainees as to what areas of the task they need to improve on (i.e., task-related feedback). Meaning, it tells them areas where their performance needs the most work in order to perform the current task better. It does not, however, tell them how to improve those areas, just that they need attention. Conversely, learning cognitive feedback reminds trainees of general (and more abstract) learning strategies (i.e., learning-skill feedback) that transcend the current task and provides feedback about how well they are implementing those strategies in the current task. Additionally, research with adaptive guidance has only examined transfer that is directly following training (e.g., Bell & Kozlowski 2002; 2008). In this transfer phase, participants were presented a more complex version of the training task but the “generalization” task did not require trainees to demonstrate training learning for encountering new ambiguous problems (i.e.,
a task where the rules of the game have changed) within the radar-tracking task and assessment of transfer was not assessed over time.

Unlike the traditional specific feedback about task information typically employed in studies of feedback specificity (e.g., Goodman et al., 2004; Goodman & Wood, 2004), learning cognitive feedback would not readily lead the recipient to correct decisions. Instead, the feedback recipient would still have to explore the task space, much like someone receiving knowledge of results feedback, but the exploration would be guided in that the recipient would receive feedback about making confounded decisions. That is, the recipient would still be actively engaging in information processing because he or she would still need to draw his or her own conclusions from the task environment because the information in the feedback message would give no indication of the underlying dynamics of the task. Additionally, repetition from applying learning cognitive feedback strategies during training would instill learning strategies in recipients, such that when a new environment is presented, the recipients could recall the principles learned from the feedback without actually needing the feedback itself. Taken together, this should keep learning cognitive feedback recipients from becoming cognitively lazy in their pursuit of discovering underlying dynamics of the task and from becoming reliant on the information contained in the feedback message.

Another advantage of learning cognitive feedback is that it would allow recipients to receive exposure to decision rules underlying poor task performance. Again, since this type of feedback does not direct recipients to correct decisions, it enables recipient to make decisions errors. Unlike specific task information feedback that hinders the
occurrence of decision errors, learning cognitive feedback cannot stop someone taking the advice of the feedback from making unconfounded wrong decisions. Following the principles of systematic exploration will likely lead the recipient to poor initial performance because only one decision can be made at any given time. Yet, over time, as the recipient begins to discover how each decision can play out in the task environment, he or she begins to understand the dynamics of the environment.

Thus, the type and nature of the specific feedback message seems paramount. Perhaps the specificity of the secondary external feedback message is not the culprit of the differential relationship with learning. Instead, the task information that makes up the content of the message is unhelpful for developing learning skills. Feedback enabling participants to understand how to learn to engage the task environment to understand it, although more specific and detailed, could lead to enhanced learning and performance in a posttraining context.

The Current Study

The present study seeks to understand the effects of learning cognitive feedback and the role of specificity on task learning. Specifically, I am interested in the effect of specificity on learning outcomes as applied to multiple types of secondary external feedback. To understand these relationships, a commonly used paradigm, the Furniture Factory is employed (Wood & Bailey, 1985). I manipulated the specificity of secondary external feedback provided during the training phase of the simulation by crossing two types of feedback in the task. Specifically, I crossed the amount of task-related feedback (task-feedback specificity) given to the participant, by the amount of learning-related
feedback (learning-feedback specificity) given. Then, I assessed learning on two separate utilizations of the same task during a transfer phase two days later. Specifically, the transfer phase of the experiment was divided into two parts. Like previous studies, in the near transfer phase, participants were asked to make decisions about employees in the Furniture Factory where the rules governing employee performance were the same as during the training phase. In the far transfer (i.e., generalization) phase, participants were asked to make more decisions about employees in the Furniture Factory. However, now they were given a new work team to manage and they were informed that the rules governing employee performance are different for this work team than they were during the training phase and the near transfer phase.

It was expected that those given the traditional operationalizations of secondary external feedback would perform typically during training. That is, those given KR (low-task feedback specificity) would underperform relative to their cognitive feedback-task information (high-task feedback specificity) counterparts during training. As previously mentioned, learning cognitive feedback promotes a systematic decision-making strategy that encourages making errors. Because of this, it was proposed that those given learning cognitive feedback (high-learning feedback specificity) would underperform relative to participants given no learning cognitive feedback (low-learning feedback specificity) during training.

**Hypothesis 1**: Training performance levels for participants receiving high-task feedback specificity will be higher than participants receiving low-task feedback specificity.
**Hypothesis 2:** Training performance levels for participants receiving low-learning feedback specificity will be higher than participants receiving high-learning feedback specificity.

Previously researchers (e.g., Goodman et al., 2004) hypothesized that low-task feedback specificity given during training should lead to better overall performance during near transfer. However, no study has yet found a performance difference during near transfer. Because of the lack of evidence for this finding, researchers have argued that the differences are most pronounced in learning the rules governing poor worker performance (Goodman & Wood, 2004). Here, studies have found that those given low task-feedback specificity during training learn the rules governing poor performance best. Additionally, I expected that participants who receive high-learning feedback specificity would perform similarly to low-task feedback specificity during near transfer and with respect to learning poor performance rules. Again, because high-learning feedback specificity encourages error-making, it was likely that those receiving this type of feedback would have more exposure to poor performance than low-learning feedback specificity recipients. To that end, I investigated both types of effects for both types of feedback specificities: 1) a main effect for task-feedback and learning-feedback specificities and 2) an interaction effect for task-feedback and learning-feedback specificities with performance rule learning during near transfer.

**Hypothesis 3:** Learning performance levels during the near transfer phase will be lower for participants who had received high-task feedback specificity than for participants who had received low-task feedback specificity during training.
Hypothesis 4: Learning performance levels during the near transfer phase will be lower for participants who had received low-learning feedback specificity than for participants who had received high-learning feedback specificity during training.

Hypothesis 5: Poor performance rule learning during near transfer will be lower for participants who had received high-task feedback specificity than for participants who had received low-task feedback specificity during the training phase.

Hypothesis 6: Poor performance rule learning during near transfer will be lower for participants who had received low-learning feedback specificity than for participants who had received high-learning feedback specificity during the training phase.

The real proposed advantage of learning cognitive feedback is for far transfer. When participants are presented with a new work team that behaves differently than the team they were trained with, then participants trained with learning cognitive feedback group should be better equipped to learn the new task dynamics. Specifically, it was anticipated that learning cognitive feedback recipients, through their more efficient understanding of learning principles for uncertain environments, obtained during training, would perform better than those not exposed to learning cognitive feedback, during the far transfer task. However, examining overall differences in performance may obscure the advantages of learning cognitive feedback. That is, at the beginning of far transfer, those who had received high learning cognitive feedback during training should perform poorly as they systematically explore the task environment. As they begin to learn and
implement decisions based on their understanding of the new task dynamics, their performance should begin to pick up, such that they begin to perform better than their low-learning cognitive feedback counterparts. Thus, any overall performance differences may prove insignificant depending on the amount of time it takes for high-learning cognitive feedback recipients to learn the new task rules. To this end, I examined far transfer performance in two ways. First, I examined the differences in overall performance during far transfer between those who did and did not receive learning cognitive feedback. Secondly, I examined the far transfer performance trajectories between those who did and did not receive learning cognitive feedback. I anticipated that if an overall performance effect was not found, then those who had received learning cognitive feedback should be trending to outperform (i.e., the performance trajectories are different) those who had not received learning cognitive feedback by the end of the far transfer phase.

**Hypothesis 7a:** Learning performance levels during the far transfer phase will be higher for participants who had received high-learning feedback specificity than for participants who had received low-learning feedback specificity during training.

**Hypothesis 7b:** The learning performance trajectory during the far transfer phase will be higher (i.e., trending toward higher performance levels) for participants who had received high-learning feedback specificity than for participants who had received low-learning feedback specificity during training.
Finally, it was expected that those receiving learning cognitive feedback would engage in more systematic and less unsystematic exploration of the task environment during the far transfer phase than those who received no learning cognitive feedback. This is because participants in this condition are directly given feedback about how they are implementing the learning strategies designed to foster systematic exploration of the task environment.

**Hypothesis 8**: Participants who had received high-learning feedback specificity will engage in more systematic, and less unsystematic, decision-making than will participants who received low-learning feedback specificity during training.
Method

Overview

Participants completed a 20-trial training task under one of four conditions of feedback. The low-task/low-learning feedback specificity condition consisted of outcome-only (KR) feedback for each trial. The low-task/high-learning feedback specificity condition (learning cognitive feedback) provided outcome-plus-specific-process feedback about learning how to perform the task during each trial. The high-task/low-learning feedback specificity (cognitive feedback-task information) provided participants with outcome-plus-specific-process feedback about the correctness of all decisions they made during each trial. The high-task/high-learning feedback specificity condition provided participants with outcome-plus-specific-process feedback about the correctness of all decisions they made, as well as specific-process feedback about learning how to perform the task during each trial. During the training phase, all participants were informed that their goal was to learn the decision rules underlying the task and to learn ways to discover those rules for future simulations. Two days later, participants completed the transfer phase to assess learning, which comprised three sets of trials with minimal feedback provided. During the transfer phase, two sets of trials were used to assess near transfer and the third set of trials was used to assess far transfer. Task performance was assessed during the training phase and during the near and far transfer phases. Learning was measured as participant performance during the transfer tasks. Systematic decision-making was also assessed during the far transfer phase.
Participants

Participants in this study were recruited via a web-based experimental management system maintained through the Psychology department from a large Midwestern University. In exchange for participation in the study, students received course credit. One hundred and four individuals completed the training phase of this experiment. Participants returned 2 days later and completed the transfer phase of this experiment, which was used to assess the learning that occurred during the training phase. Six participants were lost because of attrition from Time 1 to Time 2, reducing the Time 2 sample size to 98 (94%). Participants were 57% women, 43% men and ranged in age from 18 to 29, with a mean age of 19.76 (SD = 1.61).

Because a management decision-making simulation was used as the experimental task, I assessed participants’ management-related experience with a five-item, five-point scale, with 1 = none and 5 = very much (Goodman et al., 2004; Goodman & Wood, 2004; see Appendix A). The purpose of this assessment was to ensure that participants’ had low management-related experience before experiencing the Furniture Factory game and that no differences existed between conditions. This was necessary because participants were going to be asked to identify relationships between variables and employee performances. Preconceived notions, because of prior management experience, could make this process more difficult. Participants were asked to rate their previous experience with delegating work to others, assigning performance goals to others, setting their own performance goals, giving performance feedback to others, and rewarding others for their performance. The reliability of the five items was .82. As expected participants had only
a low to moderate amount of management related experience (M = 2.72, SD = .71), which facilitated the study of learning. No significant differences were found between conditions on overall management-related experience or on any of the individual items.

Participants were also asked to rate their self-efficacy on several aspects of the task they were about to perform. This was done to ensure that participants felt confident in their abilities to engage the experimental task and these beliefs were similar across conditions. Like the management-related experience questionnaire used above, responses were on a five-point scale, with 1 = Not Very Well and 5 = Very Well (see Appendix B). Listed below are the four questions with the mean of the responses following each question. The self-efficacy questions were: How well do you feel you can perform this managerial-decision making task (M = 3.58, SD = .76); How well do you feel that you can figure out how to perform when the rules of the simulation are ambiguous (M = 3.22, SD = .80); How well do you feel you can perform computer-based tasks (M = 3.87, SD = .98); How well do you feel you can use computers in general (M = 4.25, SD = .85). As expected, mean self-efficacy response to each of the questions was moderate to high with self-efficacy around learning the ambiguous rules the lowest. As expected, participants had moderate to high self-efficacy in their ability to perform the task. Again, no significant differences were observed between any of the self-efficacy questions across conditions.

Finally, at the conclusion of the experiment, participants were asked to rate the amount of effort they felt they had given to their performance in the experiment. Responses ranged from 1 = little effort to 5 = much effort. The mean response for amount
of effort given to the experiment across feedback specificity conditions was 3.37 with a standard deviation of .82. There were no significant differences between reported effort levels and feedback specificity condition.

**Experimental Design**

The design was a mixed $2 \times 2 \times 3 \times 20$. That is, there were two between factors (i.e., high vs. low task feedback and high vs. low learning feedback) assessed over three different phases (i.e., training, near transfer, and far transfer) with 20 different trails in each phase. Participants were randomly assigned to one of four experimental secondary external feedback conditions using block randomization (i.e., participants were randomly assigned to one of the four conditions until each condition had a participant to ensure equal numbers in each condition). The secondary external feedback conditions were: low-task/low-learning feedback specificity, low-task/high-learning feedback specificity, high-task/low-learning feedback specificity, and high-task/high-learning feedback specificity, all of which are described below. Additionally, repeated measures included multiple trials of engaging the task during three different time periods: 1) the training phase, and two days later 2) a near transfer phase and 3) a far transfer phase.

**The Task**

The study was presented as a project in managerial decision-making. Participants were asked to serve as a manager of a work team in a variation of the business simulation called the “Furniture Factory.” This simulation has been used in previous research to study the effects of feedback specificity on exploration and learning (e.g., Goodman et al., 2004; Goodman & Wood, 2004, 2007). It has also been used to study the effects of
task complexity and goal setting on self-regulation, exploration, and performance (e.g., Wood, Atkins, & Bright, 1999; Wood, Bandura, & Bailey, 1990). There are many properties of the task that contribute to the complexity and realism of the simulation. For example, in each trial there are a number of variables for participants to make decisions about and each of these variables have multiple options associated with them. The decisions that participants made about these variables, for each employee, affected future team performance levels. Also, decisions made about these variables are interdependent and have underlying rules governing their interdependence that are dynamic (i.e., changing as the conditions of the simulation being managed changes). Thus, within the simulation participants had many different alternative responses available to them and they therefore had to explore the task environment to discover or infer the underlying decision rules linking their decision actions to outcomes, under various conditions of employee performance.

These features of the simulation made it possible to create various feedback interventions that differed in their level of task relevant information (i.e., specificity). The task also provided records of all decisions that participants made and whether each decision was correct or incorrect, which was used to measure participants’ learning of specific responses to different task conditions. As previously mentioned, the “correctness” of various task decisions changed depending on task conditions. This made it possible to assess the learning of the rules for correctly responding under favorable (i.e., good or high individual performance) versus unfavorable (i.e., poor or low individual performance) task conditions.
As the manager, participants managed a group of three employees over 20 weeks of production during the training phase (Time 1). During Time 2, participants managed five employees over two sets of 10 weeks of production for the near transfer phase and three employees over 20 weeks of production for the far transfer phase (a total of 40 weeks of production). Each performance trial represented one week at the Furniture Factory and each trial participants assigned the employees to jobs and motivated them. Each of the participants’ employees was best suited for certain jobs. The participants were able to motivate their employees by providing them with goals, feedback (not to be confused with the feedback that participants received from engaging the simulation), and rewards. Additionally, they determined the level of each that they wanted to use to motivate the employees.

Participants received written instructions describing the simulation task. They were given information about their role, the skills and work-related preferences of each employee, the descriptions and requirements of each Furniture Factory job, and the choices of types of goals, feedback, and rewards they could give to their employees. Participants were told that underlying the performance of their employees are decision rules that affect employee performance. As managers, they had to learn the relationship between the jobs and motivating variables, such that they could assign employees and monitor the effects on employee performance. Thus, their task was to divine the decision rules underlying employee performance. Additionally, they were told that one work team (or set of employees) may respond differently than another work team with respect to the resultant motivation of the variables so they should pay particular attention to
inconsistencies in the relationships between motivating variables for different work teams. That is, the relationship found for one work team may not hold true for other future work teams that they may later encounter. To this end, participants should not only divine the rules, but learn how to divine the rules for future work teams.

The instructions were presented on the computer screen (see Appendix C for Time 1 instructions and Appendix D for Time 2 instructions) and each participant was given a reference sheet (see Appendix E for the Time 1 reference sheet; see Appendix F for the Time 2 reference sheet) to refer to throughout the simulation. To learn how to manage their employees well, the participants had to accurately assign employees to work tasks within the Furniture Factory, as well as figure out the correct responses for assigning the motivating variables to their employees under different task conditions, which are described below. Participants were also instructed that the decisions and actions they took on one trial would influence performance on subsequent trials. The task is dynamic and decisions made have lasting implications for the productivity levels of the work team in future trials. That is, optimal decisions are contingent on past employee performance and influence subsequent employee performance.

With the first trial, participants had four decisions to make about each of the employees in their work team. First, they had to assign each of the employees to one of the production jobs required to complete the weekly order of furniture (Figure 3). These jobs included: milling timber, assembling parts, staining and glazing assembled frames, upholstering furniture, and preparing products for shipment.
Figure 3. Assigning Employees to Production Jobs

The employees differed in their skills and preferences to perform each job and in their potential maximum performance levels once assigned to a job. During the instructions, and in the reference sheet provided, participants were told about the requirements of each of the aforementioned production jobs. They were also given a brief synopsis about each of the individual employees that hinted about what each employee’s skills and preferences were. Although the connections between employee skills and abilities and the requirements of each of the production jobs was fairly straightforward, this decision, while having some impact on performance, was not too detrimental to
employee productivity. By far, decisions regarding the motivating variables carried much more weight in calculating employee productivity for each week.

Once participants had assigned each employee to a job, they had to motivate the employees (Figure 4). First, they had to motivate them by setting a goal for each employee from a set of five options. Participants could choose to give no goal, tell the employee to do his or her best, set a goal 25% worse than the standard (low goal), set a goal equal to standard (moderate goal), or set a goal 25% better than standard (high goal).

**Figure 4. Assigning Levels of the Motivating Variables to Employees**
Participants also chose among four types of performance feedback to provide to each employee over a trial. Specifically, participants could choose to provide no feedback, discuss with the employee what he or she did correctly and incorrectly when performing the job (cognitive feedback), inform the employee of his or her performance level in relation to the standard for the job (KR feedback), or provide both types of feedback. Lastly, participants chose from a set of three reward levels for each employee. They could choose to give no reward, praise an employee (moderate reward), or publicly recognize an employee by posting a memo (high reward).

Thus, for each trial of the simulation, participants made decisions around assigning employees to jobs and deciding what type of goals, feedback, and rewards to give to each employee. Participants were also able to maintain or change any or all of their decisions from trial to trial. Table 1 summarizes the decisions that participants could make around each employee, each trial, with regard to goals, feedback, and rewards. Throughout the task, participants were trying to learn the decisions rules related to assigning employees to jobs and determining what levels of goals, feedback, and rewards to give employees based on their performance. This was achieved through engaging the task and experimenting with various combinations of motivating variables and then interpreting the feedback they received about the effectiveness of their decisions. These rules were represented in a mathematical model within the Furniture Factory simulation and were used to calculate the hours taken to complete the assigned furniture order for each trial.
Table 1.

*Participant Decisions for the Furniture Factory Employees*

<table>
<thead>
<tr>
<th>Motivating Variable</th>
<th>Possible Decisions</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Goal</strong></td>
<td>Give no goal</td>
</tr>
<tr>
<td></td>
<td>Tell the employee to &quot;do his or her best&quot;</td>
</tr>
<tr>
<td></td>
<td>Set a goal 25% worse than the standard (low goal)</td>
</tr>
<tr>
<td></td>
<td>Set a goal equal to the standard (moderate goal)</td>
</tr>
<tr>
<td></td>
<td>Set a goal 25% higher than the standard (high goal)</td>
</tr>
<tr>
<td><strong>Feedback</strong></td>
<td>Give no feedback</td>
</tr>
<tr>
<td></td>
<td>Discuss with the employee what he or she did correctly and incorrectly when performing the job (process feedback)</td>
</tr>
<tr>
<td></td>
<td>Inform the employee of his or her performance level in relation to the standard for the job (outcome feedback)</td>
</tr>
<tr>
<td></td>
<td>Provide both process and outcome feedback</td>
</tr>
<tr>
<td><strong>Reward</strong></td>
<td>Give no reward</td>
</tr>
<tr>
<td></td>
<td>Praise the employee (moderate reward)</td>
</tr>
<tr>
<td></td>
<td>Publicly recognize an employee by posting a memo (high reward)</td>
</tr>
</tbody>
</table>

Participants were given no knowledge of the mathematical formula as they learned the decision rules of the task. As participants chose correct decisions, performance improved. As participants chose incorrect decisions, performance declined. A floor and ceiling was applied to individual employee performance. Doing this meant that the worst an employee could perform was at 40% worse than the standard (i.e., only giving the task 60% effort) and the best an employee could perform was at 20% better than the standard (i.e., giving the task 120% effort). In addition to calculating individual employee performance, the model created a measure of group performance.
Two different sets of decision rules were used in the Furniture Factory simulation. The first set of decision rules described the relationship between variables leading to optimal performance in the training phase of the experiment. Similarly, this set of decision rules described the relationships for optimal performance in the first two sets of trials (i.e., near transfer phase) at Time 2 of the experiment. However, a second set of decision rules described the relationship between variables leading to optimal performance for the third set of trials (i.e., far transfer phase) at Time 2 of the experiment. Outlined below are the decisions that participant managers should have used to achieve the highest functioning from their employees on the set A decision rules and the set B decision rules.

Optimal decisions for set A decision rules. The relationship between the decisions that participants made about goals, feedback, and rewards and subsequent employee performance during the training phase (Time 1) and the two sets of trials during the near transfer phase (Time 2) was governed by the decisions rules outlined in Table 2. The optimal decisions for set A decision rules were contrived for this study. That is, they were not meant to reflect any specific research on the true relationship among these variables. When the simulation began, a difficult goal was the optimal goal choice. A difficult goal continued to be optimal goal choice until an employee experienced repeated failure. If an employee performed at or worse than the 20% of the standard (i.e., very poor performance) for two consecutive trials, a moderate goal became the optimal goal choice. If the employee performed well later in the task, then the difficult goal became the optimal choice once again. The optimal choice of moderate or high goal setting could
change back and forth throughout the duration of the simulation depending on employee performance. Decision rules for feedback and rewards, as well as goal level, can be found in Table 2.

Table 2.

<table>
<thead>
<tr>
<th>Decision Rules: Set A</th>
<th>Decision type</th>
<th>Rule description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employee job allocation</td>
<td>Assign each employee to a job on the basis of the match between job and employee characteristics.</td>
<td></td>
</tr>
<tr>
<td>Goal</td>
<td>Give the high goal initially.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Give the moderate goal after an employee performs very poorly for 2 consecutive weeks (≤ 20% worse than standard).</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Give the high goal after an employee performs better than 20% worse than standard.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Giving no goal, or the low goal is never optimal.</td>
<td></td>
</tr>
<tr>
<td>Feedback</td>
<td>Give outcome-plus-process feedback.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Give outcome-only feedback after an employee performs well (≥ standard) for 3 consecutive weeks.</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Giving no feedback, or process-only feedback is never optimal.</td>
<td></td>
</tr>
<tr>
<td>Reward</td>
<td>Give an employee no reward for poor performance (&lt; standard).</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Give the moderate reward when performance is close to standard (standard ≤ performance &lt; 5% better than standard).</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Give the high reward for good performance (≥ 5% better than standard).</td>
<td></td>
</tr>
</tbody>
</table>

Optimal decisions for set B decision rules. The relationship between the decisions that participants made about goals, feedback, and rewards and subsequent employee
performance during the last set of trials during the far transfer phase (Time 2) was governed by the decisions rules outlined in Table 3. Again, the optimal decisions for set B decision rules were contrived for this study. When the simulation began, no goal was the optimal goal choice. Giving employees no goal remained the optimal goal choice the second week as well. The optimal goal choice for the third week depended upon employee performance. If performance over the first two weeks had been worse than 10% of the standard, then a low goal became the optimal goal choice. However, if performance fluctuated between 10% below and 10% above the standard, then the moderate goal was the optimal goal choice. Setting a high goal for the employees was never an optimal goal choice. Indeed, if the employee performed better than 10% above the standard, then the participant should have given no goal to the employee. The order and effectiveness of the goal choices for this decision rule set fluctuated through all trials depending on employee performance. Decision rules for feedback and rewards, as well as goal level, can be found in Table 3.
Table 3.

**Decision Rules: Set B**

<table>
<thead>
<tr>
<th>Decision type</th>
<th>Rule description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Employee job allocation</td>
<td>Assign each employee to a job on the basis of the match between job and employee characteristics.</td>
</tr>
<tr>
<td>Goal</td>
<td>Give no goal initially.</td>
</tr>
<tr>
<td></td>
<td>Give the low goal after an employee performs very poorly for 2 consecutive weeks (≤ 10% worse than standard).</td>
</tr>
<tr>
<td></td>
<td>Give moderate goal when performance is around the standard (10% worse than standard &lt; performance &lt; 10% better than standard).</td>
</tr>
<tr>
<td></td>
<td>Give no goal when performance is high (≥ 10% better than standard).</td>
</tr>
<tr>
<td></td>
<td>Giving the high goal is never optimal.</td>
</tr>
<tr>
<td>Feedback</td>
<td>Give outcome-only feedback.</td>
</tr>
<tr>
<td></td>
<td>Give process-only feedback after an employee performs poorly (&lt; 10% worse than standard) for 3 consecutive weeks.</td>
</tr>
<tr>
<td></td>
<td>Give outcome-plus-process feedback after an employee performs well (≥ standard) for 3 consecutive weeks.</td>
</tr>
<tr>
<td></td>
<td>Giving no feedback is never optimal.</td>
</tr>
<tr>
<td>Reward</td>
<td>Give no reward when performance is very low (&lt; 20% worse than standard).</td>
</tr>
<tr>
<td></td>
<td>Give the moderate reward when performance is less than or slightly greater than the standard. (20% worse than standard &lt; performance &lt; 10% better than standard).</td>
</tr>
<tr>
<td></td>
<td>Give the high reward for good performance (≥ 10% better than standard).</td>
</tr>
</tbody>
</table>

**Manipulations**

Four levels of secondary external feedback specificity were used to examine differences between feedback specificity and subsequent learning on a transfer task. The
four levels of feedback specificity were only manipulated during the training phase of the experiment. During the transfer (i.e., learning) phases, all participants received the same low-task/low-learning feedback specificity across all three sets of trials.

**Low-task/low-learning feedback specificity.** In the low-task/low-learning feedback specificity condition, participants received KR feedback that only included the weekly job performance levels for each of their three employees as well as overall work team performance. This included several types of outcome feedback that were objective performance data (Figure 5).

![Figure 5. Low-Task Feedback Specificity Example](image-url)
Specifically, the feedback given included: the hours taken by each employee and the work group to produce the order for that trial, the estimated standard hours given the order, and a comparison that showed the percentage above or below the standard for each individual employee and for the work group. Additionally, employee and work group percentage comparisons above or below the standard were also color coded to aid in participant interpretation. Green percentages indicated work that was better than the standard while red percentages indicated work that was lower than the standard. Given this data, participants were able to assess how each employee and the work group performed relative to the estimated standards for the individual jobs and the total weekly furniture order.

Low-task/high-learning feedback specificity. In the low-task/high-learning feedback specificity condition, participants received learning cognitive feedback about how well they were implementing learning strategies in order to learn how to discover the underlying decision rules (i.e., cognitive feedback about learning). Specifically, all participants were told two strategies to discover the decision rules, but participants in this condition were given feedback about how well they were adhering to both of the two learning strategies. Participants also received the feedback described in the low-task/low-learning feedback specificity about employee and work team performance.

The first strategy that participants were told was that when trying to discover the decision rules it is best to only change one thing at a time. That is, changing the level of more than one of the motivating variables each trial, for a given employee, confounds the effects of both variables being changed making it difficult to determine the effects
responsible for changes in employee performance. After the second trial, participants were told if they did or did not change the level of more than one motivating variable for each employee (Figure 6). Thus, they could receive a message that said, “You changed the goal level and the reward level for Jack, you should only change the level of one of the motivating variables for each employee so you can see the effect of a single decision on employee productivity.” Conversely, they could receive a message that said, “Good job. You did not change the level of any of the three motivating variables for Jack.”

![Figure 6. High-learning Feedback Specificity, Screen Shot 1](image)
The second strategy that participants were told was that they should not only change one thing at a time, but also stay with that one change and monitor it over time, in order to see its effect over time. Thus, they should not only make one change, but stay with that change for several trials in order to see its long-term effect. To this end, participants also received feedback telling them if they had or had not changed the level of a variable over the previous two trials (Figure 6 – lower portion of the “Motivating Variable Feedback”). For example, they could receive a message that says, “You didn’t hold your decisions constant for Jack, Kurt, or Neil.” Alternatively, when they did not change the level of a variable for three consecutive trials, then they received a plot of employee performance over the previous three trials (Figure 7). This gave participants in this condition a visual representation of the trend effects of their actions over the single variable. Additionally, each employee was represented by a different color line in the plot. If they change another variable in addition to the constant variable they did not receive a graph after the consecutive trail because performance was then confounded. Additionally, a participant could receive a graph of performance for an individual employee. This means that if the participant followed the learning rule with Neil, but not Jack or Kurt, then the participant would receive a graph of Neil’s performance over the previous three weeks. In the meantime they would continue to receive feedback about Jack and Kurt indicating that they were not following the learning rules. Finally, if a participant continued with a set of decisions too long (i.e., failing to change any of the three motivating variables for more than three weeks for a given employee) then they received a message telling them that it
was unwise to continue with a particular set of decisions for too long unless they were confident they had learned the decision rules underlying task performance.

Figure 7. High-learning Feedback Specificity, Screen Shot 2

High-task/low-learning feedback specificity. In the high-task feedback specificity condition, participants received the low-task/low-learning feedback described above, but also received cognitive feedback-task information (Figure 8). That is, individuals in this condition received error signal feedback about their decisions. Specifically, participants
in the high-task feedback specificity condition received specific feedback about the correctness of each of the decisions they made for each of their employees.

They were told whether the job allocations, goals, feedbacks, and rewards decisions that they made for each employee was right or wrong. Thus, in addition to the KR feedback, they received 12 informational statements (3 employees × 4 decisions) about the correctness of their decisions on each trial. The statements took the form, “You assigned Bob to the wrong job,” or “You gave Jack the correct reward.”
High-task/ high-learning feedback specificity. In this condition, participants received all of the previously mentioned types of feedback. That is, in addition to the knowledge of results – outcome feedback, participants also received cognitive feedback in the form of task information – process feedback, and learning cognitive feedback – process feedback. The structure was such that participants were first presented with the learning cognitive feedback about their decisions (i.e., adherence to the learning rules), and then simultaneously the knowledge of results and cognitive feedback. However, if participants had followed the learning rules, such that they also received a graph of employee productivity, then this graph was presented at the same time they also received the knowledge of results feedback and the cognitive feedback.

Measures

Training performance. Training performance represented the percentage of hours above or below the previously set standard for the group of employees for each of the 18 trials during the training phase (Time 1). It was computed as: training performance = 1 - (actual number of hours for task completion by the group / standard number of hours). For example, if a group of employees took 35 hours to complete a furniture order that should have taken 32 hours, the groups’ performance would be computed as 1 - (35/32) = -0.0938 or 9.38% worse than the standard. Zero percent would indicate that performance was equal to the standard. Additionally, 10% would indicate performance was 10% better than the standard, while -10% would indicate that performance was 10% worse than the standard.
Learning performance. Learning was assessed during the near and far transfer phases (Time 2) of the experiment. By measuring learning at a later time with minimal feedback specificity, we assessed the extent to which the skills and task knowledge necessary for performing the task were learned during the training phase (Time 1). Assessing learning during the training phase likely consisted of not only true learning that could generalize or transfer beyond training, but also transient effects that were only apparent under the training period (Christina & Bjork, 1991; Schmidt & Bjork, 1992). The latter effects are temporary and confound measures of long-term learning when assessed via performance during the practice or training phase (Wulf & Schmidt, 1994). Using this transfer design, I was able to minimize transient effects and more accurately identify learning effects that were due to the level of feedback specificity in the training phase.

Learning was assessed in two ways for the three sets of trials in the transfer phase. First, I examined the percentage of hours above or below the previously set standard for the group of employees for each of the three sets of trials during the transfer phase (Time 2). This measurement of learning was consistent with the measure of training performance mentioned above. According to Goodman and Wood (2004) overall measures of learning obscure external feedback specificity effects because of feedback’s differential effects on the learning of correct responses to good versus poor performance. Thus, I also examined decision rule learning for good and poor performance separately for the first two sets of trials (i.e., near transfer). In the first two sets of trials, participants were asked to demonstrate their knowledge of the underlying decision rules that governed
training performance (i.e., decision rule set A). Separating responses to good and poor performance rule learning allowed me to identify if feedback specificity was beneficial for, or detrimental to, each of the these two aspects of learning. As such I created two different variables to measure both aspects of learning. However, I did not separately examine good and poor performance rule learning for the third set of trials (i.e., far transfer) during the transfer phase. During the third set of trials, participants were asked to engage a new work team where a new underlying decision rule set was employed (decision rule set B). As such, the only way to gauge the effects of learning cognitive feedback, compared to no learning cognitive feedback, is to examine the percentage of hours above or below the previously set standard for the group of employees. Again, this approach is consistent with the training measure of performance mentioned above.

To identify good and poor performance rule learning, I created two new variables consistent with Goodman and Wood (2004). The first variable, good performance rule learning, was measured during the near transfer phase and was measured for decision rule set A. Good performance rule learning comprised the first 20 trials during the transfer phase and was calculated as the percentage of instances the participant made the correct responses to good performance as stipulated by the rules listed in Table 2. To do this, I determined for each instance where the participant should have given the high goal, outcome feedback, and/or the high reward to each of his or her employees and if they responded correctly. The variable was then computed by dividing the total number of times each good performance rule was correctly applied by the total number of times each good performance rule should have been applied.
The second variable, *poor performance rule learning*, was also measured during the near transfer phase and was measured for decision rule set A. Poor performance rule learning for decision rule set A also comprised the first 20 trials during the transfer phase and was calculated as the percentage of instances the participant made the correct responses to poor performance as stipulated by the rules listed in Table 2. To do this, I determined for each instance where the participant should have given the moderate goal, process and outcome feedback, and/or no reward to each of his or her employees and if they responded correctly. The variable was then computed by dividing the total number of times each poor performance rule was correctly applied by the total number of times each poor performance rule should have been applied.

*Systematic and unsystematic exploration.* Systematic exploration represented changing only one motivating factor per trial per employee. Changing only one factor for an employee was equivalent to making an unconfounded change, which allowed the participant to identify the effects of their decision on employee performance. When more than one factor was changed during a given decision cycle, the feedback received was uninterpretable with respect to employee performance. During the far transfer phase, it was possible to engage in systematic exploration between 0 to 3 times per trial (up to one decision change for each of the three employees) for the second set of 20 trials. Across the entire transfer phase, it was possible to change decisions a minimum of 0 times and a maximum of 60 times (3 employees × 20 trials) and still be systematic. Unsystematic exploration represents making confounded decisions and is reciprocal (i.e., perfectly and inversely related) to systematic exploration. Thus, during the far transfer, it was possible
to engage in unsystematic exploration between 0 and 3 times per trial for the second 20 trials (two or three decision changes for each of the 3 employees). This again resulted in a maximum of a possible 60 instances of unsystematic observation.

Procedure

To study the effects of secondary external feedback specificity on learning, I conducted a transfer experiment that took place over two laboratory sessions. During the training phase (Time 1) I randomly assigned participants to one of the four feedback specificity conditions (i.e. low-task/low-learning, low-task/high-learning, high-task/low-learning, or high-task/high-learning feedback specificity). Participants sat at a computer station with partitions separating computer stations from each other. They performed 20 trials (i.e., work weeks) of the Furniture Factory simulation. As described above, participants were told that their goal during the training phase was to learn the rules for allocating jobs, goals, feedback, and rewards to each of their employees (three employees total). They were also instructed that the decision rules they learn for the current work team may or may not hold true for other work teams that they might manage in the future. They were instructed that they should not only learn the rules for this work team, but more generally learn how to discover the underlying decision rules for employee performance. More generally, they were instructed to learn how to learn the decision rules for the work team. During the training phase, the decision rule set A was used to govern the simulation. Participants were also instructed that they were to remain at their computer station until all other participants had finished the simulation. Everyone was dismissed when all participants had finished the task.
Participants returned to the laboratory two days later for the transfer phase of the experiment. During the transfer phase (Time 2), I assessed participant learning about how to discover the decision rules underlying employee, and by extension, work team performance in the Furniture Factory simulation. Again, the same procedure described above was implemented during the transfer phase of the experiment. Participants were told that their goal during the transfer phase was to implement what they learned from the training phase in order to increase the productivity of their employees and the work team. Like before, participants were instructed to remain at their computer station until all other participants had finished the simulation and everyone was dismissed when all participants had finished all three sets of trials.

During the near transfer phase, participants began by playing the first set of 10 trials, governed by decision rule set A. Participants managed the same work team that they previously managed in the training phase although this time there were two new employees (five employees total). This set of trials was identical to the trials they played in the training phase. That is, the employees that they managed had the same level of initial performance (i.e., slightly above standard) as in the training phase, giving participants the opportunity to demonstrate how well they learned to respond to good performance in the training phase. The only feedback that the participant managers received was low-task/low-learning feedback (i.e., knowledge of results feedback).

Next, participants played a second set of 10 trials, also governed by decision rule set A. Participants again managed the same work team as the previous set of trials (five employees total) although this time the employees started with below standard initial
performance. Starting the employees with poor initial performance allowed participants the opportunity to demonstrate how well they learned to respond to poor performance in the training phase of the experiment. Because employee initial performance was considerably low, participant managers were required to make many correct management decisions before employee performance was high enough to be governed by the good performance rule set. Again, the only feedback that participants received was the low-task/low-learning feedback. Taken together, the first and second sets of trials provided enough opportunity to identify participant learning of managing examples of good and poor performance.

Finally, during far transfer, participants played a final set of 20 trials; governed by decision rule set B. Participants were given a new work team comprised of three employees and were told that they had to discover the underlying decision rules that direct individual and team performance. Everything else in this set of trials was the same as all previous trials with the exception of the work team and the decision rules underlying their performance. The purpose of this set of trials was to ascertain the extent to which participants learned how to discover the underlying decision rules linking the motivating variables to employee performance. Participants only received low-task/low-learning feedback, consistent with the rest of the trials during the transfer phase of the experiment.

Data Analysis

To test Hypotheses 1, 2, 3, 4, and 7a a repeated-measures analysis of variance (ANOVA) was used to assess the between-subjects and within-subjects effects of
feedback specificity on training performance (measured at Time 1) and learning
(measured at Time 2, via near and far transfer), respectively. Specifically, posttests were
conducted to assess significant differences between the different feedback specificity
conditions and performance levels. Similarly, hypotheses 5 and 6 also utilized a repeated-measures analysis of variance to assess the between-subjects and within-subjects effects of feedback specificity on good performance rule learning and poor performance rule learning, both measured during the near transfer phase (Time 2). Again posttests were conducted to assess differences between feedback specificity conditions. To test Hypothesis 7b a repeated-measures analysis of variance was used to assess a within-subjects interaction of learning feedback specificity and time, within the far transfer phase. An analysis of variance was used to analyze systematic/unsystematic decision making differences between the feedback specificity conditions during the far transfer phase for Hypothesis 8.

All post hoc comparisons were conducted using the Tukey HSD. A Cicchetti
approximation (Cicchetti, 1972) was used for post hoc comparisons conducted on
interaction terms in the analysis of variance. The Cicchetti approximation is used to
adjust Tukey’s k, and by extension the q value used, by examining only unconfounded
comparisons after a significant interaction term instead of all possible comparisons.
Results

Assessment of Attrition Effects

Procedures recommended by Goodman and Blum (1996) were used to assess the effects of participant attrition on study results. Specifically, six participants were lost between the practice phase (Time 1) and the transfer phase (Time 2). Using Time 1 data, I performed multiple logistic regression to assess the presence of attrition bias, which might affect Time 2 results. The independent variables for the analysis were task feedback specificity, learning feedback specificity, and Time 1 practice performance. The dependent variable was a dichotomous variable indicating whether or not the participant came to the Time 2 transfer session of the experiment. The logistic regression analysis indicated no apparent nonrandom sampling: Model $\chi^2(3, N = 104) = 2.99$, $p = .224$. Task feedback specificity, learning feedback specificity, nor Time 1 practice performance affected whether or not participants continued participation at Time 2. Additionally, no difference was found between the Time 1 whole sample and the Time 2 participants on Time 1 practice performance, $t(100) = .248$, $p = .196$. No variance enhancement or reduction was found on Time 1 practice performance either, $z = -.13$, $p = .90$ (Hayes, 1988). Because Time 2 dependent variables (i.e., learning performance) could not be collected at Time 1, comparison of the differences in structural relationships could not be performed. However, the analyses I was able perform did not indicate attrition bias (Goodman & Blum, 1996).
Participant Performance and Task Descriptives

Correlations among the study variables as well as the total sample and cell means with standard deviations are shown in Table 4. Additionally, Figure 9 provides a graphical representation of task performance for each phase for each condition of feedback specificity. On average participants took 23.67 minutes to complete the training phase (Time 1) with a standard deviation of 9.19 minutes. The near transfer phase (Time 2) took on average 19.81 minutes to complete with a standard deviation of 7.71 minutes and the far transfer phase took on average 10.93 minutes to complete with a standard deviation of 4.02 minutes. No significant differences were found between the feedback specificity conditions and time taken to complete each of the phases.
Table 4.

**Correlations Among Variables**

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Training performance</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Near transfer performance</td>
<td>-.54 **</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Far transfer performance</td>
<td>-.28 **</td>
<td>.06</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Poor performance rule learning</td>
<td>-.30 **</td>
<td>.21 *</td>
<td>.05</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Good performance rule learning</td>
<td>.02</td>
<td>-.08</td>
<td>.01</td>
<td>.34 **</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>6. Systematic exploration</td>
<td>-.06</td>
<td>.03</td>
<td>.16</td>
<td>-.05</td>
<td>-.02</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. Unsystematic exploration</td>
<td>.06</td>
<td>-.03</td>
<td>-.16</td>
<td>.05</td>
<td>.02</td>
<td>-1.00 **</td>
<td></td>
<td></td>
</tr>
<tr>
<td>8. Feedback specificity</td>
<td>.45 **</td>
<td>-.23 *</td>
<td>.01</td>
<td>-.30 **</td>
<td>.23 *</td>
<td>-.01</td>
<td>.01</td>
<td></td>
</tr>
</tbody>
</table>

|                  | M      |        |        |        |        |        |        |        |
| Total sample     |        |        |        |        |        |        |        |        |
| (n = 104 Time 1, n = 98 Time 2)               |        |        |        |        |        |        |        |        |
| M                | -8.87  | -17.42 | -20.56 | .36    | .41    | 35.43  | 24.57  |        |
| SD               | 13.25  | 3.72   | 10.22  | .13    | .19    | 12.91  | 12.91  |        |
| Low-task/low-learning feedback specificity   |        |        |        |        |        |        |        |        |
| (n = 27 Time 1, n = 26 Time 2)                |        |        |        |        |        |        |        |        |
| M                | -13.85 | -16.54 | -22.09 | .41    | .35    | 32.69  | 27.31  |        |
| SD               | 10.52  | 3.20   | 11.03  | .14    | .20    | 12.67  | 12.67  |        |
| Low-task/high-learning feedback specificity  |        |        |        |        |        |        |        |        |
| (n = 26 Time 1, n = 25 Time 2)                |        |        |        |        |        |        |        |        |
| M                | -19.14 | -16.08 | -17.99 | .41    | .39    | 41.48  | 18.52  |        |
| SD               | 10.36  | 3.64   | 11.08  | .14    | .18    | 11.29  | 11.29  |        |
| High-task/low-learning feedback specificity  |        |        |        |        |        |        |        |        |
| (n = 27 Time 1, n = 23 Time 2)                |        |        |        |        |        |        |        |        |
| M                | 1.59   | -19.17 | -20.75 | .31    | .46    | 31.91  | 28.09  |        |
| SD               | 9.32   | 4.06   | 10.64  | .11    | .18    | 12.16  | 12.16  |        |
| High-task/high-learning feedback specificity |        |        |        |        |        |        |        |        |
| (n = 24 Time 1, n = 24 Time 2)                |        |        |        |        |        |        |        |        |
| M                | -2.80  | -18.10 | -21.39 | .32    | .45    | 35.46  | 24.54  |        |
| SD               | 11.62  | 3.34   | 7.82   | .09    | .18    | 13.92  | 13.92  |        |

Note. *Coding: low-task/low-learning = 1, low-task/high-learning = 2, high-task/low-learning = 3, high-task/high-learning = 4.*

* p < .05. ** p < .01.
Figure 9. Feedback Specificity Performance Across Trials
Tests of Hypotheses

Hypotheses 1, 2, 3, and 4 were all tested with Tukey HSD posttests from the same omnibus test. The omnibus test of these hypotheses was a 2 (low vs. high task feedback) × 2 (low vs. high learning feedback) × 3 (training phase, near transfer phase, and far transfer phase performance). The repeated measures analysis of variance violated the assumption of sphericity so the Greenhouse – Geisser correction was applied to the degrees of freedom (Howell, 2002). In this test there was a significant between-subjects main effect for task feedback specificity, $F(1,94) = 29.00, p < .001, \eta^2 = .24$, a significant within-subject task feedback specificity × phase interaction, $F(1.55,145.46) = 27.46, p < .001, \eta^2 = .23$, and a significant within-subject learning feedback specificity × phase interaction, $F(1.55,145.46) = 3.34, p < .05, \eta^2 = .03$ (Table 5). The significant main effect for task feedback specificity indicates that overall (performance collapsed across phases) those receiving high-task feedback specificity performed better than those receiving low-task feedback specificity (M = -13.44, SE = .56; M = -17.62, SE = .54). The two latter interactions mentioned above, allowed me to conduct the requisite post hoc analyses to test each of the aforementioned hypotheses. Specifically, the significant task feedback specificity × phase interaction allowed comparisons for Hypotheses 1 and 3 while the significant learning feedback specificity × phase interaction allowed comparisons for Hypotheses 2 and 4.

Hypothesis 1 and Hypothesis 2 both dealt with performance differences between feedback specificity conditions during the training phase of the experiment. In Hypotheses 1, I predicted that training performance levels for those receiving high-task
feedback specificity would be higher than those receiving low-task feedback specificity.

Through post hoc comparisons, Hypothesis 1 was supported. During the training phase, participants receiving high-task feedback specificity had significantly higher performance levels ($p < .05$, $d = 1.60$) than their low-task feedback specificity counterparts ($M = -.61$, $SE = 1.53$; $M = -16.50$, $SE = 1.47$, respectively). In Hypothesis 2, I predicted that training performance levels for those receiving low-learning feedback specificity would be higher than those receiving high-learning feedback specificity. Hypothesis 2 was not supported. Participants receiving low-learning feedback specificity did not have significantly different ($p > .05$) performance levels than their high-learning feedback specificity.

---

**Table 5.**

*Repeated Measures Analysis of Variance: The Effects of Feedback Specificities on Performances*

<table>
<thead>
<tr>
<th>Source</th>
<th>SS</th>
<th>MS</th>
<th>F</th>
<th>df's</th>
<th>$\eta^2$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Between subjects</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Task Feedback Specificity</td>
<td>1280.00</td>
<td>1280.00</td>
<td>29.00 ***</td>
<td>1.94</td>
<td>0.24</td>
</tr>
<tr>
<td>Learning Feedback Specificity</td>
<td>44.85</td>
<td>44.85</td>
<td>1.02</td>
<td>1.94</td>
<td>0.01</td>
</tr>
<tr>
<td>Error</td>
<td>4149.14</td>
<td>44.14</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Within subjects</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Phase</td>
<td>7601.59</td>
<td>4912.20</td>
<td>41.34 ***</td>
<td>1.55,145.46</td>
<td>0.31</td>
</tr>
<tr>
<td>Phase x Task Feedback Specificity Condition</td>
<td>5050.46</td>
<td>3263.64</td>
<td>27.46 ***</td>
<td>1.55,145.46</td>
<td>0.23</td>
</tr>
<tr>
<td>Phase x Learning Feedback Specificity Condition</td>
<td>614.97</td>
<td>397.4</td>
<td>3.34 *</td>
<td>1.55,145.46</td>
<td>0.03</td>
</tr>
<tr>
<td>Phase x Task Feedback Specificity Condition</td>
<td>122.97</td>
<td>79.46</td>
<td>0.67</td>
<td>1.55,145.46</td>
<td>0.01</td>
</tr>
<tr>
<td>Error</td>
<td>17286.74</td>
<td>118.84</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. $N = 98$. *$p < 0.05$, ***$p < 0.001$
counterparts during training (M = -6.13, SE = 1.50; M = -10.97, SE = 1.50, respectively).

In summary, from this set of analyses, we find that participants receiving high task feedback specificity performed similarly to other studies (e.g., Goodman et al., 2004; Goodman & Wood, 2004). That is, they performed significantly better than the low-task feedback specificity recipients. Interestingly, high-learning feedback specificity recipients performed similarly to low-learning feedback specificity recipients.

Hypothesis 3 and Hypothesis 4 both dealt with performance differences between the feedback specificity conditions during the near transfer phase (Time 2) of the experiment. In Hypotheses 3, it was predicted that learning performance levels during the near transfer phase would be lower for those who had received high-task feedback specificity than those who had received low-task feedback specificity during training.

Hypothesis 3 was not supported. During the near transfer phase, high-task feedback specificity recipients did not have significantly different performance levels ($p > .05$) from their low-task feedback specificity counterparts (M = -18.64, SE = .52; M = -16.31, SE = .50, respectively). Similarly, in Hypothesis 4 it was predicted that learning performance levels, during the near transfer phase, for those who had received low-learning feedback specificity would also be lower than those who had received high-learning feedback specificity. Hypothesis 4 was also not supported. Again, participants receiving low-learning feedback specificity did not have significantly different performance levels ($p > .05$) from their high-learning feedback specificity counterparts during training (M = -17.86, SE = .51; M = -17.09, SE = .51).
Although there were no significant differences between the high-task feedback specificity groups and the low-task feedback specificity groups, the means were in the hypothesized directions (Figure 9). As previously mentioned, no study to date has been able to find the hypothesized learning performance effect between high and low-task feedback specificity. With this in mind, I turn to the next set of hypotheses that have been used to demonstrate learning advantages for receiving minimal feedback.

Given the inability to find near transfer performance differences between low-task and high-task feedback specificities, researchers have examined differences in exposure to and learning of decision rules governing good and poor performance (Goodman & Wood, 2004). Specifically, these studies have found that although those receiving high specificity feedback tend to learn the decision rules governing good performance better, those receiving low specificity feedback actually learn decision rules governing poor performance better. With this in mind, Hypothesis 5 and Hypothesis 6 both dealt with poor performance rule learning differences between feedback specificity conditions during the near transfer phase (Time 2).

Hypotheses 5 and 6 were both tested with the same omnibus test. In this test there was a significant within-subject performance rule (good vs. poor performance rule learning) effect, \( F(1,94) = 8.716, p < .05, \eta^2 = .09 \), which indicated that participants, across all conditions, had better good performance rule learning than poor performance rule learning. Additionally, there was a significant within-subject task-feedback specificity \( \times \) performance rule interaction, \( F(1,94) = 26.65, p < .001, \eta^2 = .22 \), but the learning-feedback specificity \( \times \) performance rule interaction was not significant, \( F(1,94) \).
In Hypotheses 5, I predicted that poor performance rule learning levels, during the near transfer phase, for those who had received high-task feedback specificity would be lower than those who had received low-task feedback specificity during the training phase. Hypothesis 5 was supported. Participants who had received high-task feedback specificity had significantly lower poor performance rule learning ($p > .05$, $d = .83$) than their low-task feedback specificity counterparts ($M = .32$, $SE = .02$; $M = .41$, $SE = .02$, respectively).

*Figure 10.* Feedback Specificity Conditions and Good vs. Poor Performance Rule Learning
Similarly, in Hypothesis 6 I had predicted that poor performance rule learning levels during the near transfer phase would also be lower for those who had received low-learning feedback specificity than those who had received high-learning feedback specificity during the training phase. Hypothesis 6 was not supported. As previously mentioned, the learning feedback specificity × performance rule interaction was not significant. Participants receiving high-learning feedback specificity did not significantly differ in their poor performance rule learning compared to their low-learning feedback specificity counterparts during transfer (M = .42, SE = .03; M = .40, SE = .03, respectively).

Additional post hoc analyses revealed differences among task-feedback specificity conditions and good performance rule learning as well. Indeed, Goodman and Wood (2004) found significant differences between low and high-task feedback specificity conditions on learning good performance rules. As mentioned earlier, they found that participants who had received high-task feedback performed better than participants who had received low-task feedback when a good performance decision rule needed to be applied during the near transfer phase. The results of this study are consistent with their findings. Specifically, those who had received high-task feedback specificity correctly applied good performance rules significantly more ($p < .05, d = .56$) than those who had received low-task feedback specificity (M = .46, SE = .03; M = .37, SE = .03, respectively).

Hypothesis 7a dealt with performance differences between the feedback specificity conditions during the far transfer phase (Time 2) of the experiment.
Specifically, it was predicted that learning performance levels for those that had received high-learning feedback specificity during training would be higher than those who had not. Hypothesis 7a was not supported. Although, the phase × learning feedback specificity interaction was significant, $F(1.55,145.46) = 3.34, p < .05, \eta^2 = .03$ (Table 5), the post hoc comparisons revealed no significant differences for far transfer performance. That is, participants who had received high-learning feedback did not have significantly different performance levels ($p > .05$) from their low-learning feedback specificity counterparts ($M = -19.69, SE = 1.47; M = -21.42, SE = 1.47$, respectively). While the difference between the means of the high-learning feedback specificity groups and the low-learning feedback specificity groups was nonsignificant, the means were in the predicted direction (Figure 9).

As mentioned, the mean difference between the high and low learning feedback groups was not significant, but the differences were in the predicted direction (i.e., high learning feedback specificity recipients performed better than low learning feedback specificity recipients). Given the lack of an overall performance difference, for reasons previously outlined, the purpose of Hypothesis 7b was to see if there were differences between the performance trajectories of the two groups. That is, while both groups may perform similarly at the beginning of the far transfer phase, I expected that by the end of the far transfer phase high learning feedback recipients would outperform their low learning feedback counterparts. Hypothesis 7b was supported. At the beginning of the far transfer phase, participants began to engage and explore the task and make decision errors. As such, the performance levels of both groups quickly dropped. As time in the
task progressed and the performance deficits for both groups grew, those who had received high-learning feedback specificity eventually began to diverge from those who had received low-learning feedback specificity. Those who had been guided by learning feedback began to show improvements in task performance and eventually began to perform better (Figure 11).

*Figure 11. Learning Feedback Specificity Performance During Far Transfer*

Again, the repeated measures analysis of variance violated the assumption of sphericity so the Greenhouse – Geisser correction was applied to the degrees of freedom (Howell, 2002). A significant within-subjects learning feedback condition × trial
interaction provided support for the hypothesized difference in performance trajectories, 

\[ F(2.68,251.77) = 3.06, p < .05, \eta^2 = .03. \]  

Additionally, post hoc comparisons revealed significant differences between high and low learning feedback specificity recipients for several trials during the far transfer phase. Again, as expected, these significant differences were all found toward the end of the far transfer phase. Specifically, high learning feedback specificity recipients significantly outperformed low learning feedback specificity recipients during performance trials 17 (\( M = -22.20, SE = 1.87 \); \( M = -26.26, SE = 1.88 \), respectively), 18 (\( M = -20.90, SE = 1.92 \); \( M = -24.94, SE = 1.92 \), respectively), and 19 (\( M = -20.61, SE = 1.87 \); \( M = -25.28, SE = 1.88 \), respectively). Trials 16 (\( M = -21.58, SE = 1.92 \); \( M = -25.02, SE = 1.92 \)) and 20 (\( M = -22.30, SE = 1.81 \); \( M = -25.89, SE = 1.82 \)) were very close to statistical significance.

Lastly, Hypothesis 8 dealt with differences between feedback specificity conditions and systematic and unsystematic exploration during the far transfer phase. Specifically, Hypothesis 8 predicted that those in the high-learning feedback specificity condition would engage in more systematic exploration and, conversely, less unsystematic exploration of the new decision rule set than the other groups. Hypothesis 8 was supported. An analysis of variance revealed a significant between-subjects main effect for learning-feedback specificity on systematic exploration, 

\[ F(1,94) = 8.13, p < .05, \eta^2 = .08. \]  

This revealed that participants in the high-learning feedback specificity conditions engaged in significantly more systematic exploration and less unsystematic exploration than those who had received low-learning feedback specificity (\( M = 38.83, SE = 1.75 \); \( M = 31.72, SE = 1.78 \)).
Discussion

The purpose of this study was to examine the relationship between feedback specificity and learning when using learning cognitive feedback. In the cognitive task-learning literature, researchers have long argued that cognitive, or process, feedback high in specificity leads to higher learning and better posttraining transfer (Balzer et al., 1989; Kluger & DeNisi, 1996). However, with the reconceptualization of the transfer construct (i.e., having more time to pass before assessing learning) researchers have begun to provide findings inconsistent with popular theorizing for cognitive task learning (Goodman & Wood, 2007; Goodman, et al., 2004; Goodman & Wood, 2004). These studies show that high levels of feedback specificity might provide too much guidance to learners, such that they do not experience as broad range of task conditions as do their low feedback specificity counterparts. This leads to different types of task learning, as well as the general conclusion that less is often more where feedback is concerned.

Until now, however, studies have only examined the provision of task-related feedback. In the current study, the role of learning cognitive feedback in learning was examined. That is, participants were encouraged to make decisions consistent with abstract learning principles and some were give specific feedback on how well they were applying those learning principles. I expected that this feedback would provide strong guidance for learning how to learn for oneself, irrespective of the conditions of the task. This, in turn, would benefit posttraining transfer beyond that of low feedback specificity. To test this, I conducted a study where task-related feedback was crossed with learning-related feedback and learning was assessed on a similar transfer task (near transfer) and a
generalization task (far transfer) two days after initial training. Across the training and near transfer phases of this study, I fully replicated Goodman’s findings regarding the guidance function of different levels of feedback specificity (Goodman, et al., 2004; Goodman & Wood, 2004). That is, those with highly specific task feedback performed better than the low task specificity group on the learning measure, but no differently on the near transfer measure. However, results of this study also indicate that learning-related feedback provided learning guidance to trainees, but only after far transfer phase learning performance trajectories were examined. Below I begin by talking about the methodological issues that have haunted this literature and the issue of performance trajectories specifically. Then, I discuss the theoretical and practical implications of this study.

Methodological Issues

The history of the study of feedback effects on learning has been muddled because of poor construct validity in learning measures (Schmidt, et al., 1989). Assessing the level of original learning from training by separating transient and true learning effects via the passage of time between training and transfer measures changed many of the historical conceptions for effective training methods (e.g., Christina & Bjork, 1991; Salmoni et al. 1984; Schmidt & Bjork 1992; Schmidt, et al., 1989). This past research was a step in the right direction and has shown the pitfalls of examining training validity during the actual training. More recently, research has elaborated the construct validity problem and shown that overall task performance, assessed during a transfer phase days after training, may still be too gross of a measure to capture adequately training effects
(Goodman et al., 2004; Goodman & Wood, 2004). If we are not careful we can miss what is actually occurring as a result of training when relying on a general performance measure to assess learning. Indeed, Goodman’s research, and the replication of that work here, has demonstrated that although learning differences are not present in overall performance differences, they are found in performance rule learning for task-related feedback specificities. That is, different levels of feedback specificity lead to different levels of feedback guidance and different levels of exposure (i.e., opportunities to learn) under different task conditions. This exposure translates into learning different aspects of task performance (i.e., poor performance rule learning for those receiving little task feedback and good performance rule learning for those receiving high task feedback). In the same vein, in this study it was found that overall performance differences did not exist between learning-related feedback specificities, but that differences did exist in the amount of systematic observation employed in the far transfer phase. Taken together, current thinking on the construct validity of learning has been to not only assess learning separate from training, but also not to rely solely on overall measures of performance when assessing successful transfer (i.e., learning).

Results from this study extend, and further complicate, notions about the construct validity of learning measures. This study demonstrates that not only should researchers pay attention to the two issues mentioned above (i.e., time between training and transfer; identifying underlying mechanisms that might indicate learning), but also that they should pay attention to the time in which trainees are allowed to demonstrate learning in the transfer phase. That is, the amount of time given to trainees to engage the
transfer task represents a potential confound in the construct validity of overall task performance learning measures.

Indeed, when I examined learning beyond the overall measure of far transfer performance and instead examined performances within the far transfer phase, some evidence of learning due to learning cognitive feedback was found. Specifically, differences in the trajectories of performance were observed at the end of the far transfer phase. Although this was only a modest learning effect, it does indicate that learning cognitive feedback recipients were performing better than other participants in a couple of the final trials. Indeed, as predicted, the systematic exploration at the beginning of the phase led to poor performance, but then led to some improved performance as the decision rules were learned and implemented. Those who had not received learning cognitive feedback also suffered from poor performance at the beginning of the far transfer phase while they explored the task environment, but their performance never improved, probably because they never uncovered the underlying decision rules for the task. The overall result of this dynamic process is that the overall measure of task performance did not show learning effects because performance differences between the two groups were only present toward the end of the far transfer phase. That is, it took learning cognitive feedback recipients the majority of the assessment trials to learn the underlying decision rules, but once they had, their trajectory of performance began to change, such that they’re performance levels stopped trending downward. If more trials had been assessed, it could have been possible that performance levels might have further improved and an overall performance difference for the far transfer phase might have
been found. Alternatively, rather than improving, they could have simply asymptotyped. However, had fewer trials been assessed, then the performance differences observed in this study may not have surfaced at all. Yet, in either case, recipients had learned from training. The dynamic nature of the task and implementation of the learning principles created a complicated transfer environment, which required a more finely tuned measure of learning if effects were to be observed. Taken together, the results of this study imply that future feedback research should not underestimate the potential confound that time within the transfer phase exerts in the construct validity of learning measures.

Theoretical Implications

The role of feedback in learning has been widely studied with varied results and conclusions (Kluger & DeNisi, 1996). As mentioned previously, lack of construct validity in learning measures has been a major culprit in the lack of understanding of feedback effects. Although, historic prescriptions for the use of feedback have advised that specific feedback is necessary for learning (e.g., Balzer et al., 1989), more recent research has demonstrated that this is not necessarily the case for cognitive task learning (Goodman & Wood, 2004; Goodman, et al., 2004). The conclusion of this work has been that feedback provides a strong guidance function that may or may not take the trainees where the trainers want them to go. With this in mind, high specificity feedback has been described as less useful than low specificity feedback depending on what is to be trained (i.e., when tasks are complex). Yet, this more recent research must be qualified because of a restriction placed on the examination of only task-related feedback messages. In the current study, the feedback specificity and learning relationship was elaborated by
changing not only the amount of specificity provided in the feedback message, but also by changing the content of the feedback message. Specifically, guidance effects of feedback were examined when the content of the feedback message provided involved learning cognitive feedback (i.e., changing from task-related to learning-related messages).

I believe the results of this study provide good news for the use of high specificity feedback for achieving long-term transfer and learning. Specifically, high learning cognitive feedback specificity recipients learned more as demonstrated through different performance trajectories during far transfer and the systematic exploration of the task environment. This provides some evidence that feedback can be used to guide trainees to learn for themselves when confronted with an environment that they were not specifically trained for. Indeed, this study further confirms what others have already been saying, that high specificity feedback provides a substantial guidance function for learning (e.g., Christina & Bjork, 1991; Goodman & Wood, 2004; Goodman, et al., 2004; Saloni et al. 1984; Schmidt & Bjork 1992; Schmidt, et al., 1989). However, where past researches have cast this guidance in a negative light, because of the narrow (i.e., restrictive) learning of task properties that high specificity feedback typically leads to, the results of this study imply that high amounts of guidance can actually be a good thing. By changing the content of the feedback message, high feedback specificity guidance was used to train principles that were transferred and implemented in the far transfer task. Thus, it appears that the usefulness and effectiveness of feedback for learning will depend on the design of the feedback message.
Feedback that does not support training principles in its message is not useful to trainees. This was demonstrated in the finding that performances between traditional operationalizations of feedback specificity (i.e., for task-related feedback) were indistinguishable during the far transfer phase. However, feedback that has been intentionally designed with both the transfer environment and the learning principles for the training in mind can focus (i.e., guide) trainees to learn with positive results. Intentionally designing feedback requires having some understanding of the transfer environment where you want to see performance affected, and then identifying the skills that could influence performance and can be trained (Goldstein & Ford, 2002). The content of the feedback message presented during training should then reinforce the development of these skills, which is the purpose of training. In this study, the transfer environment was one where trainees needed to engage and explore the task environment in a systematic way in order to understand the underlying mechanics of the complex and dynamic task environment. Thus, the content of the feedback message reinforced and supported the training of abstract learning principles that were designed to accommodate the complexity and uncertainty of the transfer environment. By recognizing that feedback provides guidance to learn and the content of the message can be designed to support the learning of the trained skills, positively reframes the feedback specificity and learning relationship.

Previous research has missed the recognition of the usefulness of feedback guidance because, as mentioned above, the feedback interventions often employed have been too narrow in conceptualization. This means that the feedback messages provided
(i.e., task-related feedback) have not matched the demands of the dynamic transfer environment. Indeed, in Goodman’s research, the high feedback specificity messages provided have been too narrow and, in turn, lead to very narrow types of learning. It is not necessarily surprising that these types of messages were not effective given the nature of the performance environment that researchers wanted trainees to perform in. This research has been useful for understanding the effect feedback guidance can have when left undirected by the trainer. However, because feedback guidance can be directed and affected by the trainer, a new useful research opportunity in this paradigm would be to maintain the content of the feedback message while changing the training environment to match the types of task learning required for performance in the transfer environment. That is, provide high specificity task-related feedback across the entire domain of possible task performance conditions, during training. Instead of allowing the guidance of feedback to dictate what task performance conditions recipients are exposed to, research could examine what happens to transfer and learning when feedback recipients are forced to be exposed to both favorable and unfavorable task conditions. It seems reasonable to believe that given the guidance of feedback, recipients would outperform those not provided guidance to learn both types of task performance conditions in transfer, but this is an empirical question.

Lastly, it is worth noting that learning cognitive feedback effects were not present for near transfer performance. However, this is not necessarily surprising for two reasons. First, those who had received learning cognitive feedback were not guided to learn the specific decision rules underlying task performance in the training environment. Instead,
the feedback they received guided them to learn how to systematically explore the task environment in order to learn the underlying decision rules for themselves. That is, the guidance they received was more focused on developing systematic decision-making skills and less focused on the specific decision rules underlying task performance. Given this emphasis it is seems reasonable that learning the specific decision-rules for the training phase would be more difficult, or nonexistent, because of its secondary focus. Secondly, the results of the far transfer phase showed that performance trajectories were needed to examine learning differences between low and high learning cognitive feedback recipients. Additionally, differences between groups did not surface until approximately three fourths of the way through the far transfer phase (around trial 15 or so). The near transfer phase was structured, such that participants were given opportunities to demonstrate learning of task decision rules under favorable and unfavorable task conditions in two different utilizations of the transfer task. They were given 10 trials of favorable task conditions and 10 trials of unfavorable task conditions in which to perform. Given the performance trajectory finding it is not unreasonable to suspect that overall performance differences as well as performance trajectory differences would not surface because participants were not given enough time to perform in either of the two task conditions in the near transfer phase. If more trials of each task condition were assessed it seems reasonable to believe that differences in systematic exploration would have surfaced and performance trajectories would be different.

In summary, this study contributes to the theoretical understanding of the feedback specificity and learning relationship by demonstrating that feedback guidance
can be used to positively affect learning. Feedback does what it is designed to do and guides trainees to learn. To that end, researchers and trainers alike should take care to intentionally design the content of the feedback message so that it can be used to its advantage in helping engender the desired learning principles.

Limitations and Future Research

The research paradigm employed in this study presents some strengths and limitations with respect to the generalizability of the findings to other tasks and environments. Specifically, the computer simulated decision-making environment allowed for the control necessary for internal validity. Also, it allowed me to objectively manipulate feedback specificities and measure learning. The manipulation of feedback represented a range of specificity and types through varying the content of the task-relevant and learning-relevant information in the feedback message. The level of experimental control, for this study, was appropriate because the purpose of the study was to identify causal relationships.

In this laboratory study, the emphasis on internal validity in the design raises the question of whether these results generalize to other more natural environments. For example, the decisions that participants were asked to make in the task were well structured and readily available during the simulation. In applied settings this may often not be the case. Instead, individuals may have many potential courses of action to take, some of which they may not be even aware of or know are available to them. In addition to the structure of the task environment, all participants in the current study were college students with little to no managerial decision-making experience. This was an advantage
because the naiveté allowed for more potential learning to occur. However, it may limit the generalizability of the results because they are not trainees in an organizational training setting. The population and contest to which this study seeks to generalize is individuals in the workforce who are recipients of training programs. Fortunately, several researchers argue, and meta-analytic findings confirm, that laboratory findings with student samples often complement field findings with nonstudent samples (Anderson, Lindsay, & Bushman, 1999; Greenberg, 1987; Locke, 1986). Furthermore, previous laboratory research on effects of objective feedback has provided some evidence that feedback effects found in the laboratory do generalize to natural work settings (Kopelman, 1986). However, the effectiveness of learning cognitive feedback should be examined in other, more applied settings.

In addition to examining effects in applied settings, the effects of learning cognitive feedback specificity on learning should also be examined with other types of cognitive tasks. In this study, participants engaged a contrived complex and dynamic environment where performance dictated future courses of action. The properties of the environment were unknown to participants and required searching the task space for clues as to how decisions should be made. Although guided learning, via learning cognitive feedback, proved useful in this context, it should also be examined with other types of cognitive tasks. Indeed, this study demonstrates that the content of the feedback message was able to guide learners in their learning of a few abstract learning principles. Future research should examine if the effects observed in this study were a product of the type of task (e.g., task properties) utilized or if guided learning could provide a learning
benefit on other types of trained tasks. That is, would guided learning transfer to other
types of decision-making and cognitive tasks.

Another consideration of this study includes the fact that feedback specificity
came in one of two levels (i.e., low and high). In applied settings, individuals can receive
potentially limitless levels of feedback specificity depending on the task and the source of
the feedback. In this study, it was impossible to examine any curvilinear relationship
between feedback specificity and learning because of the artificial restriction of feedback
specificity to two levels. With respect to task-related feedback, some past research has
included multiple levels of feedback and has shown that no curvilinear relationship exists
(Goodman & Wood, 2004; Goodman et al., 2004). Yet, future research needs to examine
the linearity of learning cognitive feedback specificity and task learning.

Finally, in this experiment all feedback came from one source, namely the
computer. Whereas computer-provided feedback is becoming more common, as
computer-based training becomes more popular, there are other sources where
individuals can receive feedback (Goodman et al., 2004). Indeed, for many tasks, primary
feedback is readily available, although this was not the case in this study. In addition to
secondary feedback from the task, there are also a myriad of human sources that could
provide feedback to individuals. Feedback from each of these relational sources can be
interpreted based on their motives for providing the feedback (Illgen et al., 1979) as well
as their credibility in providing the feedback (Fedor, 1991). It may be presumptuous to
assume that impersonal computerized feedback operates similarly to feedback from
human sources. Future research should examine other sources of feedback, both in terms
of the availability of primary feedback from the task environment as well as other external and more personal sources.

Practical Applications and Conclusion

In this study, I found that different types of feedback (e.g., task-related or learning-related) and the level of specificity of feedback given to trainees during training can lead to different types of learning and transfer. To that end, the findings of this study are useful to practitioners designing feedback interventions for training. Recognizing that high feedback specificity provides a strong guidance function for learning and that feedback messages can be designed to reinforce training principles is practically useful for enhancing the positive effects of training for transfer.

Specifically, learning cognitive feedback was used to compliment and reinforce instruction about general learning principles provided at the beginning of training. This feedback guided recipients to learn general learning principles that aided recipients’ performance in a future unknown task environment through the development of systematic decision-making strategies. To the extent that someone might want to train an individual to perform in a similar unknown environment where individuals need to engage and explore the task space in order to perform well, then the specific feedback used here might be useful. However, on a broader scale, this study demonstrates that learning-related types of feedback can be developed to enhance the learning of abstract principles that can later aid performance in a post-training context. That is, by understanding some aspects of the environment that training is to transfer to, trainers can develop feedback that supports the learning of general abstract learning principles that
can improve transfer performance in a given environment. The high specificity learning feedback used in this study is but one example of a learning-related type of feedback.

If, however, one wanted to train an individual for a task environment where the dynamics of the environment never changed and were well understood, then learning cognitive feedback would probably be unnecessary. In this instance, one could proceed with a cognitive, process, feedback (i.e., task-related) approach and train the recipients on all aspects of the transfer environment. That is, use high specificity feedback to guide trainees to learn all aspects of the transfer task. Thus, the usefulness of learning cognitive feedback ends at the point where the nature of the performance environment is well understood. However, jobs of this type are becoming fewer and far between with most reviewers of the field arguing that the trend for more complexity at work will continue to grow (e.g., Goldstein & Ford, 2002).

The results of this study further add to the understanding of the relationship between feedback specificity provided during training and subsequent learning. Specifically, previous qualifications to the feedback specificity learning relationship, with respect to task-related feedback, were replicated in this study. Additionally, support for the usefulness of learning cognitive feedback in a far transfer generalization task was found. Guidance resulting from the provision of learning-related feedback provided additional benefit to learning beyond the provision of task-related feedback. Indeed, participants receiving learning cognitive feedback performed better and engaged in more systematic exploration of the task environment than those that did not receive learning cognitive feedback. This study contributes to the understanding of feedback intervention
effects on learning outcomes by demonstrating the nuance of the specificity question.
Whereas traditional thinking regarding feedback specificity has produced results
demonstrating that more specific feedback is better and leads to greater outcomes, recent
research has said that less can be better depending on the types of skills one wishes to
engender in trainees. Results from this study further elaborates the feedback specificity-
learning relationship by demonstrating that more specificity can again be better when the
nature of the feedback is learning-related instead of task-related for unknown
environments. Thus, prescriptions about feedback specificity still need to be qualified in
accordance to the type of feedback provided, the skills to be trained, and the future
environments where those skills will be employed.
References


Appendix A: Management-related Experience Questionnaire

### Before We Begin...
Identify the option that best describes your experience with each of the following statements. Click the button at the bottom of the page when you have made a selection for each of the statements.

<table>
<thead>
<tr>
<th>Task Description</th>
<th>None</th>
<th>A Little</th>
<th>A Moderate Amount</th>
<th>Quite A Bit</th>
<th>Very Much</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Delegating work to others?</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Assigning performance goals to others?</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Setting your own performance goals?</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Giving performance feedback to others?</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Reviewing others for their performance</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Begin The Task!
Appendix B: Self-efficacy Questionnaire

A Few More Questions...

Identify the option that best describes your experience with each of the following statements. Click the button at the bottom of the page when you have made a selection for each of the statements:

How well do you feel you can learn how to perform this managerial decision-making task?
- Not Very Well
- Very Well

How well do you feel that you can figure out how to perform when the rules of the situation are ambiguous?
- Not Very Well
- Very Well

How well do you feel that you can perform computer-based tasks?
- Not Very Well
- Very Well

How comfortable are you with using computers in general?
- Not Very Well
- Very Well

Begin Furniture Factory
Appendix C: Time 1 Instructions

SESSION 1: INTRODUCTION

Thank you for coming.

As you know, this is a two part experiment. Today, during the first part of the experiment, you will be performing a simulated task on the computer called the Furniture Factory. Over the next several pages, you will read instructions about the simulation and get familiar with your role in the Furniture Factory. You should have been given a reference sheet that details some of the information that is going to be presented. If you have not been given a reference sheet, please ask the experimenter for one now.

THE FURNITURE FACTORY: INTRODUCTION

The Furniture Factory is a business simulation designed to investigate the effect of different kinds of management information on decision making performance. As the player, you are the factory's Special Order Manager, responsible for allocating employees to jobs and motivating them so as to complete the weekly special order list in as short a time as possible.

The Furniture Factory manufactures furniture, but it also restores furniture in the Special Order Department (i.e., your department). The Special Order Department operates on a weekly cycle. Each week you will receive a Job Requirements Manifest (this will appear on the screen), showing the estimated work hours in each job category required to complete the special order for the following week. Your job is to ensure that the weekly special order requirements are produced efficiently. Efficient production is achieved by minimizing the actual time spent on special orders in comparison to the estimated times.

Each week you will have several tasks to complete to achieve production efficiency. These tasks are:

1) Assign employees to jobs based on the match between their skills and the requirements of the job.
2) Set production goals for each employee.
3) Provide performance feedback to each employee.
4) Allocate rewards to each employee within discretionary limits.

The process of recording each of these decisions will become obvious when you begin the simulation. Once you start the simulation, simply follow the instructions provided and use the provided reference sheet to aid in your decision-making.
What Determines Production Efficiency?

The jobs that must be performed to complete the work for the week vary in nature. Some are interesting, some are dull, some require special skills, and some require attention to detail. The employees also vary in their skills and aptitudes, and in their attitudes and their motivation for different jobs.

The actual time an employee takes to complete a job depends in part on the match between the employee's abilities and the skill requirements of the job, and in part on the employee's motivation to do the job well. Employee abilities and job skill requirements cannot be changed, but motivation can be affected by the way you set production goals, provide feedback about past performance, and give rewards. These three factors influence motivation, which can positively influence individual employee performance and group production efficiency.

As the Special Order Manager, your task is to:
1) Identify the correct match between employee skills and abilities to those required by the different jobs.
2) Learn the underlying relationships between the three motivating variables (production goals, performance feedback, and rewards) and employee performance in order to increase the overall production efficiency of your work team.

In the future you may become the Special Order Manager for other work teams. It is noteworthy that not all teams respond to the motivating variables in the same way; they may affect employee performance differently in your future work team than they do in the team you are assigned to today. Thus, you should not only learn the relationship between the motivating variables and performance for this particular work team, but you should more generally learn how to learn the relationships so that you can effectively use these variables for your future work team.

Management Information Provided

To assist you in making decisions, the following information is available on your reference sheet:

1. Descriptions of the jobs that might be required for a special order. Different orders may require different combinations of jobs from the following set of eight different kinds of jobs:
   Rough Milling – Raw timber is cut to approximate size & defects removed. This job is routine, requiring the employee to constantly repeat the same actions.
Finish Milling - Rough-cut timber is finished, ready for assembly. It requires attention to detail, the ability to recognize flaws in the wood, and the ability to use machinery.

Assembly - Finished timber is assembled. It requires woodworking skills and careful thought to put wood pieces together.

Finishing - Assembled furniture is stained, sealed & glazed. This is a routine task that requires following predetermined steps to prepare finished furniture for sale.

Fabric Cutting - Upholstery material is cut to pattern. Employees need only follow the guidelines of the pattern to accomplish this task.

Sewing - Cut material is sewn. This task requires attention to detail and skill in working with a sewing machine in order to create crisp and straight seams.

Upholstery - Sewn material, padding & springs fixed to furniture. This task requires attention to detail and upholstery skills. Each piece is different and requires the ability to develop solutions for different types of problems.

Warehouse - Storage & movement of finished goods. This task is routine and requires moving finished goods to predetermined places in the warehouse.

2. Details of employees, including skills and aptitudes. The three employees listed will be available for the Special Order Roster from week to week:

Jack - is one of the firm's oldest employees. He has been a builder for most of his working life, so he has a wide range of general woodworking skills. He has a healthy distrust of these new fancy machines', although he is a competent lathe operator, and he is happiest with non-technical, manual jobs.

Kurt - has just joined the company from school. He has a range of woodworking skills, but he lacks experience. He takes a reasonable amount of care with his work and has a fine eye for detail.

Neil - has been with the company for only a few years. He is a seamstress and dressmaker by training, but was made redundant when his previous employer got into financial difficulties. He takes a pride in his work, both in his furniture covers and the dressmaking and embroidery which occupy his evenings.

Beginning the Simulation

Each week you will begin by assigning each employee to one of the required jobs for the week. To do this, you will type the employee number, listed below the Job Requirements Manifest, next to the job you want to assign them. No employee can be assigned to more than one job. Once you have assigned employees to jobs you will click on the “Assign Employees” button to confirm your assignment. After employees have been assigned you will notice the employee name next to the job you assigned them.
Next, you will motivate your employees to perform their best on their assigned jobs in order to achieve production efficiency. Employees can be motivated with the assignment of three different variables.

1. Setting Production Goals
   These may be set in various ways, at different levels of difficulty and preciseness.
   
   Available options are:
   1) Give no performance goal
   2) Set a goal 25% easier than estimated time (low goal)
   3) Set a goal equal to the estimated time (moderate goal)
   4) Set a goal 25% harder than estimated time (high goal)

2. Providing Performance Feedback
   Different forms of performance feedback may be provided.
   
   Available options are:
   1) No feedback provided
   2) Discuss with the employee what he or she did correctly or incorrectly when performing the job (process feedback)
   3) Inform the employee of his or her performance level in relation to the standard for the job (outcome feedback)
   4) Provide the employee both process and outcome feedback

3. Allocating Rewards
   You may distribute minor day-to-day rewards.
   
   Available options are:
   1) No reward provided
   2) Compliment the employee on good performance (moderate reward)
   3) Post a memo in the break room acknowledging the employee's contribution (high reward)

To motivate employees, you must select one option from each of the three categories presented on the previous page for each employee. There are several strategies that you can use that will help you make decisions during the simulation. One strategy is that you should only change one thing at a time. Each week you will make decisions about goal, feedback, and reward levels for each employee. You should only change the level of one of these variables each week, for a given employee and keep the other levels constant. If you change more than one, you will not be able to observe its impact on employee performance. It is also important to observe the impact of a decision over time. That is, you should observe the effect that a decision has on employee performance over a three week period.
Once you have made your decisions, then press the “Fill Order” button and you will immediately receive feedback about how well each employee performed, relative to the estimated hours for each job. Additionally, you will receive feedback about how well the work team performed, relative to estimated hours for the team. You will be given employee and work team performance in terms of the raw number of hours it took them to complete their tasks. Also, you will be given a percentage for each employee and the work group that reflects individual and group efficiency in task performance. Specifically, a percentage of 100% means that actual performance equaled estimated performance. A percentage above 100% means that actual performance was more than estimated performance (e.g., it took longer to complete the task than was estimated). A percentage below 100% means that actual performance was less than estimated performance (e.g., it took less time to complete the task than was estimated). Thus lower percentages are better than higher ones. To help you remember the difference, percentages at or below 100% will be green and percentages greater than 100% will be red.

**Additional Instructions for Cognitive Feedback condition:** You will also receive specific feedback about the correctness of each of the decisions you made for each of the employees. You will be told if the job allocation, goal, feedback, and reward that you gave to each employee was the right or wrong choice.

**Additional Instructions for Learning Cognitive Feedback condition:** You will also receive feedback about how well you are implementing the two learning strategies described above (e.g., 1-changing only one decision at a time while holding other decisions constant, 2-observing the effect of a decision over time).

**Additional Instructions for Cognitive Feedback X Learning Cognitive Feedback condition:** You will also receive specific feedback about the correctness of each of the decisions you made for each of the employees. You will be told if the job allocation, goal, feedback, and reward that you gave to each employee was the right or wrong choice. You will also receive feedback about how well you are implementing the two learning strategies described above (e.g., 1-changing only one decision at a time while holding other decisions constant, 2-observing the effect of a decision over time).

Once you have been given feedback about your performance as the Special Order Manager, you will begin a new simulation week and make the above decisions again for a new order. The process should become obvious after you make a few weeks worth of decisions.
The simulation will cycle through 20 work weeks with a new furniture order for each week and you will manage a work team of 3 employees. You should continue until the full number of cycles has been completed and the game ends automatically.

Good Luck!

END OF SESSION 1

Thank you for participating in the first part of the experiment. It is very important that you also participate in the second part because I will not be able to use what you did today unless you complete both parts of the experiment. Remember that you will receive two experiment credits when you complete the second session of the experiment.

PLEASE DO NOT DISCUSS THIS EXPERIMENT WITH ANYONE ELSE. IN THIS EXPERIMENT THERE ARE MULTIPLE TYPES OF FEEDBACK PROVIDED TO PARTICIPANTS. DISCUSSING YOUR EXPERIENCE WITH OTHERS COULD AFFECT THE RESULTS OF THOSE RECEIVING OTHER TYPES OF FEEDBACK.

THANK YOU!!
SESSION 2: INTRODUCTION

Thank you for coming.

Today, during the second part of the experiment, you will be performing the same simulated task on the computer called the Furniture Factory. Over the next several pages, you will read instructions about the simulation to again become familiar with your role in the Furniture Factory. You should have been given a reference sheet that details some of the information that is going to be presented. If you have not been given a reference sheet, please ask the experimenter for one now.

THE FURNITURE FACTORY: INTRODUCTION

The Furniture Factory is a business simulation designed to investigate the effect of different kinds of management information on decision making performance. As the player, you are the factory's Special Order Manager, responsible for allocating employees to jobs and motivating them so as to complete the weekly special order list in as short a time as possible.

The Furniture Factory manufactures furniture, but it also restores furniture in the Special Order Department (i.e., your department). The Special Order Department operates on a weekly cycle. Each week you will receive a Job Requirements Manifest (this will appear on the screen), showing the estimated work hours in each job category required to complete the special order for the following week. Your job is to ensure that the weekly special order requirements are produced efficiently. Efficient production is achieved by minimizing the actual time spent on special orders in comparison to the estimated times.

Each week you will have several tasks to complete to achieve production efficiency. These tasks are:

1) Assign employees to jobs based on the match between their skills and the requirements of the job.
2) Set production goals for each employee.
3) Provide performance feedback to each employee.
4) Allocate rewards to each employee within discretionary limits.

The process of recording each of these decisions will become obvious when you begin the simulation. Once you start the simulation, simply follow the instructions provided and use the provided reference sheet to aid in your decision-making.
What Determines Production Efficiency?

The jobs that must be performed to complete the work for the week vary in nature. Some are interesting, some are dull, some require special skills, and some require attention to detail. The employees also vary in their skills and aptitudes, and in their attitudes and their motivation for different jobs.

The actual time an employee takes to complete a job depends in part on the match between the employee's abilities and the skill requirements of the job, and in part on the employee's motivation to do the job well. Employee abilities and job skill requirements cannot be changed, but motivation can be affected by the way you set production goals, provide feedback about past performance, and give rewards. These three factors influence motivation, which can positively influence individual employee performance and group production efficiency.

As the Special Order Manager, your task is to:

1) Identify the correct match between employee skills and abilities to those required by the different jobs.
2) Learn the underlying relationships between the three motivating variables (production goals, performance feedback, and rewards) and employee performance in order to increase the overall production efficiency of your work team.

It is noteworthy that not all teams respond to the motivating variables in the same way; they may affect employee performance differently depending on the work team you oversee.

Management Information Provided

To assist you in making decisions, the following information is available on your reference sheet:

1. Descriptions of the jobs that might be required for a special order. Different orders may require different combinations of jobs from the following set of eight different kinds of jobs:
   - Rough Milling – Raw timber is cut to approximate size & defects removed. This job is routine, requiring the employee to constantly repeat the same actions.
   - Finish Milling - Rough-cut timber is finished, ready for assembly. It requires attention to detail, the ability to recognize flaws in the wood, and the ability to use machinery.
Assembly - Finished timber is assembled. It requires woodworking skills and careful thought to put wood pieces together.
Finishing - Assembled furniture is stained, sealed & glazed. This is a routine task that requires following predetermined steps to prepare finished furniture for sale.
Fabric Cutting - Upholstery material is cut to pattern. Employees need only follow the guidelines of the pattern to accomplish this task.
Sewing - Cut material is sewn. This task requires attention to detail and skill in working with a sewing machine in order to create crisp and straight seams.
Upholstery - Sewn material, padding & springs fixed to furniture. This task requires attention to detail and upholstery skills. Each piece is different and requires the ability to develop solutions for different types of problems.
Warehouse - Storage & movement of finished goods. This task is routine and requires moving finished goods to predetermined places in the warehouse.

2. Details of employees, including skills and aptitudes. For the first half of today’s simulation you will work with the same work team you previously had plus the addition of two more employees. The relationship between the motivating variables and employee performance is the same for this work team as it was during the first session. The five employees listed will be available for the Special Order Roster from week to week:

Jack - is one of the firm's oldest employees. He has been a builder for most of his working life, so he has a wide range of general woodworking skills. He has a healthy distrust of these new fancy machines', although he is a competent lathe operator, and he is happiest with non-technical, manual jobs.

Kurt - has just joined the company from school. He has a range of woodworking skills, but he lacks experience. He takes a reasonable amount of care with his work and has a fine eye for detail.

Neil - has been with the company for only a few years. He is a seamstress and dressmaker by training, but was made redundant when his previous employer got into financial difficulties. He takes a pride in his work, both in his furniture covers and the dressmaking and embroidery which occupy his evenings.

Bill - is slow and placid. He has tried his hand at woodworking and upholstery, but he is not interested in detailed work and has acquired few skills in either area. He works best when performing undemanding, routine activity, requiring little thought.

Janice - is a first-class upholsterer. She began in the trade as her father's assistant, in his small furniture repair shop, and supplemented this practical apprenticeship with evening classes in upholstery and woodwork. She is meticulous in her approach. Upholstery is her forte.
Beginning the Simulation

Each week you will begin by assigning each employee to one of the required jobs for the week. To do this, you will type the employee number, listed below the Job Requirements Manifest, next to the job you want to assign them. No employee can be assigned to more than one job. Once you have assigned employees to jobs you will click on the “Assign Employees” button to confirm your assignment. After employees have been assigned you will notice the employee name next to the job you assigned them.

Next, you will motivate your employees to perform their best on their assigned jobs in order to achieve production efficiency. Employees can be motivated with the assignment of three different variables.

1. Setting Production Goals
   These may be set in various ways, at different levels of difficulty and preciseness.

   Available options are:
   1) Give no performance goal
   2) Set a goal 25% easier than estimated time (low goal)
   3) Set a goal equal to the estimated time (moderate goal)
   4) Set a goal 25% harder than estimated time (high goal)

2. Providing Performance Feedback
   Different forms of performance feedback may be provided.

   Available options are:
   1) No feedback provided
   2) Discuss with the employee what he or she did correctly or incorrectly when performing the job (process feedback)
   3) Inform the employee of his or her performance level in relation to the standard for the job (outcome feedback)
   4) Provide the employee both process and outcome feedback

3. Allocating Rewards
   You may distribute minor day-to-day rewards.

   Available options are:
   1) No reward provided
   2) Compliment the employee on good performance (moderate reward)
   3) Post a memo in the break room acknowledging the employee's contribution (high reward)
To motivate employees, you must select one option from each of the three categories presented above for each employee. Once you have made your decisions, then press the “Fill Order” button and you will immediately receive feedback about how well each employee performed, relative to the estimated hours for each job. Additionally, you will receive feedback about how well the work team performed, relative to estimated hours for the team. You will be given employee and work team performance in terms of the raw number of hours it took them to complete their tasks. Also, you will be given a percentage for each employee and the work group that reflects individual and group efficiency in task performance. Specifically, a percentage of 100% means that actual performance equaled estimated performance. A percentage above 100% means that actual performance was more than estimated performance (e.g., it took longer to complete the task than was estimated). A percentage below 100% means that actual performance was less than estimated performance (e.g., it took less time to complete the task than was estimated). Thus lower percentages are better than higher ones. To help you remember the difference, percentages at or below 100% will be green and percentages greater than 100% will be red.

Once you have been given feedback about your performance as the Special Order Manager, you will begin a new simulation week and make the above decisions again for a new order. The process should become obvious after you make a few weeks worth of decisions.

The simulation will be divided into three parts. In the first and second parts the simulation will cycle through a set of 10 work weeks each with a new furniture order for each week. During this time you will manage the work team mentioned above of five employees. During the third part of the simulation you will be given a new work team made up of three employees. This phase will consist of a set of 20 work weeks. You should continue until the full number of cycles for each part has been completed and the game ends automatically.

Good Luck!

END OF SESSION 2

Thank you for participating in the second part of the experiment.

PLEASE DO NOT DISCUSS THIS EXPERIMENT WITH ANYONE ELSE. IN THIS EXPERIMENT THERE ARE MULTIPLE TYPES OF FEEDBACK PROVIDED TO PARTICIPANTS. DISCUSSING YOUR EXPERIENCE WITH OTHERS COULD AFFECT THE RESULTS OF THOSE RECEIVING OTHER TYPES OF FEEDBACK.

THANK YOU!!
**REFERENCE SHEET – Session 1**

**Important**

Your job is to ensure that the weekly order requirements are produced efficiently. To do this, you must learn how to effectively manage and motivate your employees. Remember that the motivating variables may affect work teams differently. Thus, you should learn how to learn the relationships between the motivating variables and performance, such that you can use your strategies for future work teams that you may encounter.

Each week you must... assign employees to jobs based on the match between their skills and the requirements of the job... set production goals for each employee... provide performance feedback to each employee... allocate rewards to each employee.

Here are the descriptions of the eight different jobs in the Furniture Factory. Different jobs will be necessary for different orders.

- **Rough Milling** – Raw timber is cut to approximate size & defects removed. This job is routine, requiring the employee to constantly repeat the same actions.

- **Finish Milling** - Rough-cut timber is finished, ready for assembly. It requires attention to detail, the ability to recognize flaws in the wood, and the ability to use machinery.

- **Assembly** - Finished timber is assembled. It requires woodworking skills and careful thought to put wood pieces together.

- **Finishing** - Assembled furniture is stained, sealed & glazed. This is a routine task that requires following predetermined steps to prepare finished furniture for sale.

- **Fabric Cutting** - Upholstery material is cut to pattern. Employees need only follow the guidelines of the pattern to accomplish this task.

- **Sewing** - Cut material is sewn. This task requires attention to detail and skill in working with a sewing machine in order to create crisp and straight seams.

- **Upholstery** - Sewn material, padding & springs fixed to furniture. This task requires attention to detail and upholstery skills. Each piece is different and requires the ability to develop solutions for different types of problems.

- **Warehouse** - Storage & movement of finished goods. This task is routine and requires moving finished goods to predetermined places in the warehouse.

Below is a description of each of the three workers in your work team for the first part of the simulation.

- **Jack** - is one of the firm's oldest employees. He has been a builder for most of his working life, so he has a wide range of general woodworking skills. He has a healthy distrust of these new
fancy machines', although he is a competent lathe operator, and he is happiest with non-technical, manual jobs.

Kurt - has just joined the company from school. He has a range of woodworking skills, but he lacks experience. He takes a reasonable amount of care with his work and has a fine eye for detail.

Neil - has been with the company for only a few years. He is a seamstress and dressmaker by training, but was made redundant when his previous employer got into financial difficulties. He takes a pride in his work, both in his furniture covers and the dressmaking and embroidery which occupy his evenings.

PLEASE FEEL FREE TO MAKE MARKS ON THIS SHEET OR MAKE YOUR OWN NOTES
REFERENCE SHEET – Session 2

****Important****
Your job is to ensure that the weekly order requirements are produced efficiently. To do this you must learn how to effectively manage and motivate your employees. Remember that the motivating variables may affect work teams differently. Thus, you should learn how to learn the relationships between the motivating variables and performance, such that you can use your strategies for future work teams that you may encounter.

Each week you must…assign employees to jobs based on the match between their skills and the requirements of the job…set production goals for each employee…provide performance feedback to each employee…allocate rewards to each employee.

Here are the descriptions of the eight different jobs in the Furniture Factory. Different jobs will be necessary for different orders.

- **Rough Milling** – Raw timber is cut to approximate size & defects removed. This job is routine, requiring the employee to constantly repeat the same actions.

- **Finish Milling** - Rough-cut timber is finished, ready for assembly. It requires attention to detail, the ability to recognize flaws in the wood, and the ability to use machinery.

- **Assembly** - Finished timber is assembled. It requires woodworking skills and careful thought to put wood pieces together.

- **Finishing** - Assembled furniture is stained, sealed & glazed. This is a routine task that requires following predetermined steps to prepare finished furniture for sale.

- **Fabric Cutting** - Upholstery material is cut to pattern. Employees need only follow the guidelines of the pattern to accomplish this task.

- **Sewing** - Cut material is sewn. This task requires attention to detail and skill in working with a sewing machine in order to create crisp and straight seams.

- **Upholstery** - Sewn material, padding & springs fixed to furniture. This task requires attention to detail and upholstery skills. Each piece is different and requires the ability to develop solutions for different types of problems.

- **Warehouse** - Storage & movement of finished goods. This task is routine and requires moving finished goods to predetermined places in the warehouse.

Below is a description of each of the five workers in your work team for the first and second parts of the simulation.
Jack - is one of the firm's oldest employees. He has been a builder for most of his working life, so he has a wide range of general woodworking skills. He has a healthy distrust of these new 'fancy machines', although he is a competent lathe operator, and he is happiest with non-technical, manual jobs.

Kurt - has just joined the company from school. He has a range of woodworking skills, but he lacks experience. He takes a reasonable amount of care with his work and has a fine eye for detail.

Neil - has been with the company for only a few years. He is a seamstress and dressmaker by training, but was made redundant when his previous employer got into financial difficulties. He takes a pride in his work, both in his furniture covers and the dressmaking and embroidery which occupy his evenings.

Bill - is a new employee. He has tried his hand at basic woodworking, but has been largely unsuccessful with anything other than assembly work. He has few skills in other areas and is not motivated to learn new tasks. He is best used for organizing orders before selling them.

Jenn - is a first-class upholsterer. She began in the trade as her father's assistant, in his small furniture repair shop, and supplemented this practical apprenticeship with evening classes in upholstery and woodwork. She is meticulous in her approach. Upholstery is her forte.

Below is a description of each of the three workers in your work team for the third part of the simulation.

Bert - is a carpenter by training, with a range of woodworking skills. He does not always seem very interested in fine or detailed work, though he is capable of it, preferring less demanding jobs if given the choice.

Rose - is a new employee who enjoys fabric cutting and is able to perform simple sewing tasks. She has few skills in other areas and is not motivated to learn new tasks.

John - has been with the company for a few years now. He began as a general carpenter, but he is now highly skilled in most forms of woodwork, and is starting to learn some upholstery work. He is highly motivated, and works quickly and carefully.

PLEASE FEEL FREE TO MAKE MARKS ON THIS SHEET OR MAKE YOUR OWN NOTES