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14. ABSTRACT
Prior research in this program established that team performance is a consequence of how individuals allocate resources to accomplish multiple goals. This project extended that work around two primary research foci. The first focus built on our prior research on feedback as a means to influence *dynamic* resource allocation and adaptation. Resource allocation is a promising mechanism to explain performance adaptation to unexpected environmental perturbations. In general, the findings indicate that priming resource allocation and providing more rapid feedback updating on goal-performance discrepancies enhanced situation assessment, strategy selection, and performance adaptation. Both interventions have implications for training design and embedded decision aids. The second focus unpacked the resource allocation process by examining the dynamic interplay among the core elements of goals, effort, and performance over time. Although our prior research demonstrated that these elements were responsible for individual and team performance, the dynamic interplay was not addressed. Modeling these dynamics over time yielded important insights that will enable improved human performance in complex task domains. In particular, this extension of our research paradigm enables more precise modeling of the limits and wide variance of human performance for dynamic resource allocation. This serves as a basis for more accurate evaluation of experimental interventions designed to improve multiple goal regulation and performance adaptation, and to develop formal models of that process.

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Dynamic Resource Allocation and Adaptability in Teamwork

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Dynamic Resource Allocation and Adaptability in Teamwork

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Background, Research Objectives, and Approach

Problem Background

Team performance and adaptability. A team is a set of two or more people who interact, dynamically, interdependently, and adaptively toward a common and valued goal, each having specific roles or functions to perform, and a limited life-span of membership (Salas, Dickinson, Converse, & Tannenbaum, 1992). We assume that all cognition originates within the individual. Therefore, to understand adaptive team processes it is important to understand the ways in which being a team member affects individual cognitive processes. We also assume that unique collective constructs and processes emerge at the team level from the dynamic interaction of team members that do not exist at the individual level of analysis, despite arising from individual cognition (Kozlowski & Bell, 2003; Kozlowski & Klein, 2000). Finally, we focus on interdependent tasks in which team performance is a weighted function of actions taken by team members to accomplish both individual and team goals (Shiflett, 1979; Steiner, 1972).

Many critical command, control, and communication activities are accomplished by individuals operating in teams and interacting via complex, computer-mediated systems. These dynamic decision making task environments place high demands on operator skills and capabilities. Such tasks are dynamic, ambiguous, and emergent. They necessitate rapid situation assessment, prioritization, and strategy implementation. And, they require that individuals and teams adapt their performance as the situation shifts and unfolds—often unexpectedly. A key factor underlying this dynamic process of assessment, prioritization, and adaptability rests on the capability of individuals to appropriately allocate limited cognitive and behavioral resources to accomplish multiple goals that contribute to effective individual and team performance, and to shift their resource allocations to meet dynamic task demands. This task structure is consistent with Steiner's (1972) most general type of team task (i.e., a discretionary task), in which team members have latitude in terms of *how* and *how much* of their personal resources they allocate to accomplish team performance (Shiflett, 1979). Such teams require each member to assume individual goals, but to also coordinate effort and provide assistance to other team members to meet distinct team objectives. That is, it is the responsibility of individual team members to make resource allocation decisions that contribute to the team, such as choosing to coordinate collective effort, back-up a teammate, or aid a teammate in resolving a problem. The degree to which members allocate attention and effort across both individual and team goals is discretionary, but critical to team performance.

Deciding how to best allocate limited cognitive and behavioral resources across the multiple goals is a fundamental requirement that team members must continuously evaluate. Moreover, making good decisions about allocating limited resources is critically dependent upon monitoring where one stands with respect to the desired goal states *and* monitoring where one's teammates stand. Investing limited resources toward the achievement of individual goals may not represent a good decision if there are large discrepancies between the team goal and actual team performance. Moreover, decisions as to which team members ought to shift resources to the team goal will be more effective to the extent that individuals with the smallest individual goal discrepancies make the shift. Therefore, dynamic monitoring of multiple goal states and discrepancies with respect to current performance, and making good decisions as to team member resource allocation are central to effective team regulation and resource allocation.

Theoretical foundation. Self-regulation theory is the dominant paradigm for research on the allocation of attention and effort, and the initiation and control of action. Although there are several different models of self-regulation, the models converge around key features of a process that sketches the paradigm. Individuals regulate their attention and effort (i.e., allocate resources) around goals, monitor goal accomplishment via feedback, and make adjustments in strategies and effort to reduce discrepancies between goals and current performance. This approach has developed a broad base of empirical support as a general model of

psychological processes that underlie human learning, motivation, and performance (e.g., Karoly, 1993; Pintrich, 2003).

Virtually all of the research on self-regulation has focused on individuals striving to achieve *single goals*. Yet, working in a team requires the dynamic regulation of individual cognitive and behavioral resources with respect to *multiple goals*, both individual and team. This means that the critical process of how individuals dynamically allocate their resources around multiple goals has been substantially neglected in the literature. Moreover, the fact that individuals allocate attention and effort around multiple goals in the team context means that *regulatory processes in teams are multilevel*. Yet, most research targeted at improving team performance either focuses only on the individual level, ignoring the nesting of individuals within the team context, or on the team level as a collective, ignoring the distinctive contributions of individuals to team processes and outcomes. Our research has treated team regulation and performance as multilevel phenomena that are modeled at both levels simultaneously. Our research program has developed and empirically validated a multiple goal, multilevel model of individual and team regulation that integrates and resolves these two critical gaps in the literature (DeShon et al., 2004).

We first developed a conceptualization of the influence of multiple goals--individual and team--on feedback loops underlying the regulation of individual attention and allocation of behavioral resources. Figure 1 presents a model of how interdependent feedback loops result in the regulation of behavior with respect to both individual and team goals. In this model, two feedback loops have distinct individual and team goals that compete for control of the individuals' behavior. The feedback loop for the individual goal monitors individual-level discrepancies between current performance and goal states and activates behavioral outputs needed to reduce the discrepancy. The team feedback loop operates similarly on the individuals' team goals to activate behavioral outputs needed to reduce team-level discrepancies. The behavioral output from each of the feedback loops affects the performance levels being regulated by the other feedback loop, such that reducing discrepancies for one of the feedback loops will often result in increased discrepancies on the other feedback loop. Finally, the initial characteristics of the situation and subsequent changes in the situation may result in increased discrepancies or increased salience of discrepancies on one or both of the feedback loops. As a result, initial aspects of the situation and changes in the situation may bias the control of behavior toward reducing discrepancies at either the team or individual level.

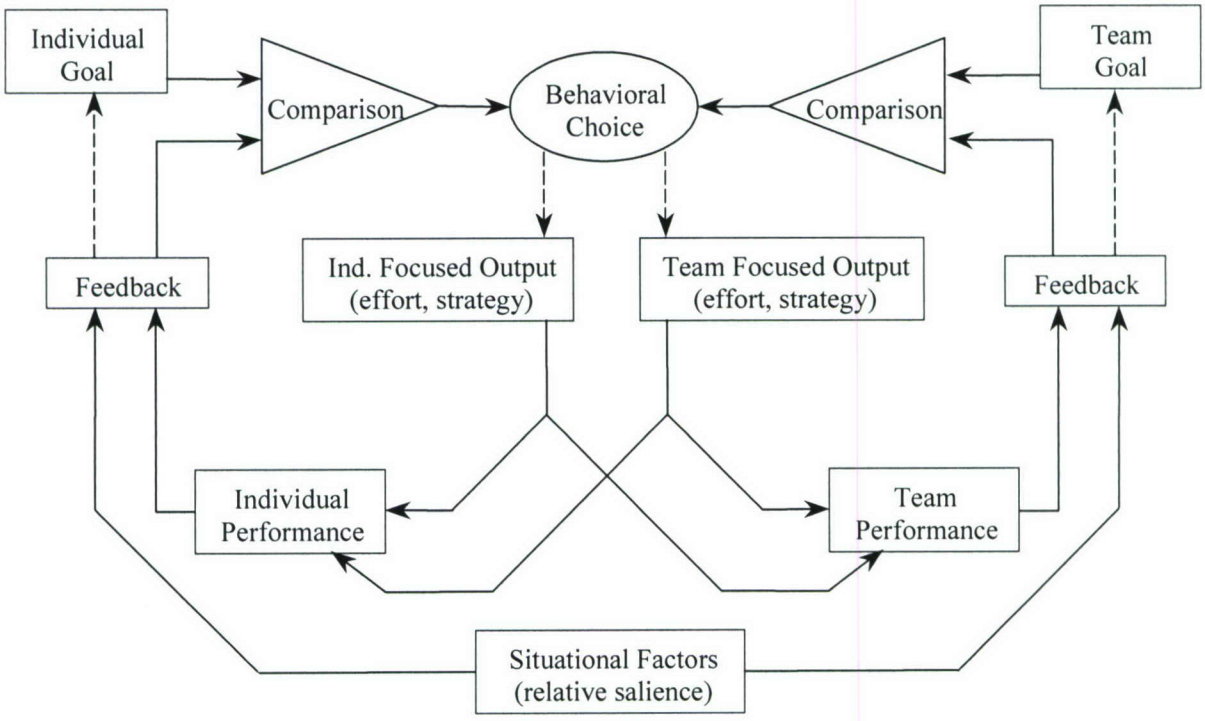
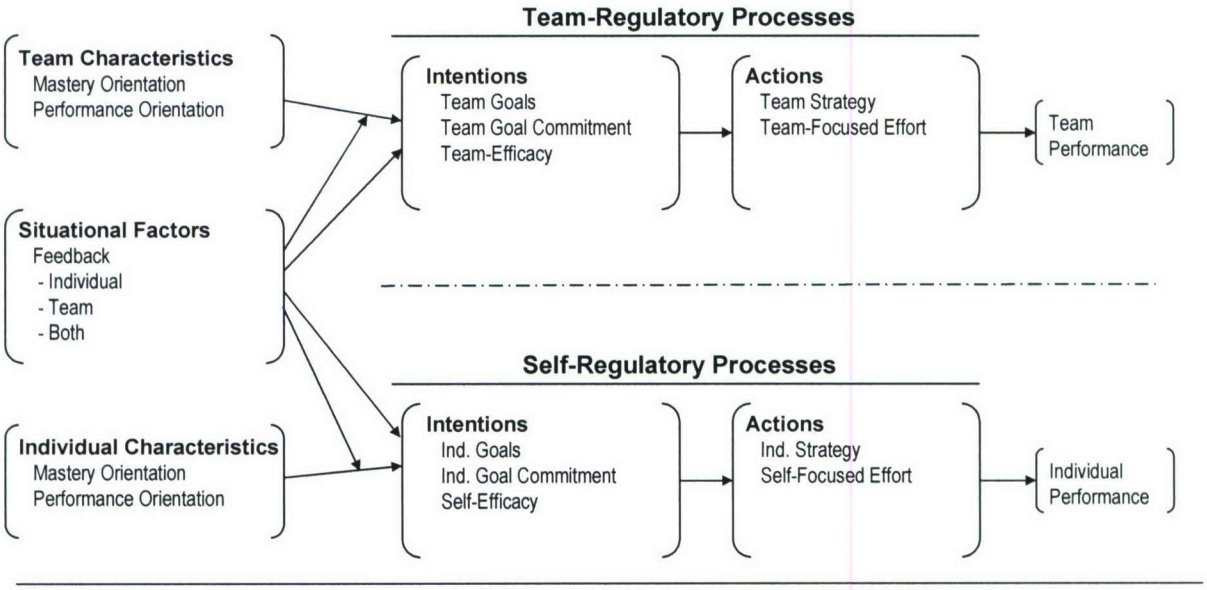


Figure 1. A multiple goal model of self-regulation.

Next, we extrapolated the dynamic self-regulatory implications of the multiple goal resource allocation model to develop a multilevel model that captured regulatory processes at both the individual and team levels shown in Figure 2 below. The essential characteristics required to validate a multilevel model are (a) that team-level constructs, conceptually parallel to those at the individual level, satisfy statistical criteria to support composition (i.e., aggregation) to the team level, and (b) that the linkages among parallel constructs at both levels demonstrate functional equivalence via configural invariance (Kozlowski & Klein, 2000). In an experimental design that examined 237 trainees organized into 79 teams of 3, DeShon et al. (2004) provided empirical support for the multilevel model shown in Figure 2 and, indirectly, for the multiple goal model shown in Figure 1. Of particular importance, the relative salience of either individual or team goal-feedback loops was the primary factor driving team member resource allocations and, ultimately, both individual and team performance.

In essence, our research demonstrated that the key regulatory processes responsible for individual resource allocation, skill acquisition, and performance also substantially hold at the team level. Scientifically we validated a *homologous multilevel model* which, to the best of our knowledge, has not been accomplished in prior empirical work (DeShon et al.,2004).



NOTE: Constructs above dashed line represent *team*-level constructs. Constructs below line represent *individual*-level constructs.

Figure 2. A multilevel model of self- and team-resource allocation and regulation.

Research Objectives and Approach

Objectives. The validation of this integrated model means that key aspects of team skill acquisition and performance, those that originate and emerge from parallel individual-level self-regulatory processes, can be effectively modeled in a multiple goal research paradigm where goals reference individual and team resource allocation (or any other multiple goals that compete for resources). Having established a theoretical foundation for the importance of individual-level multiple goal resource allocation to team learning and performance, the next logical step is to focus more precisely on the dynamics of the regulation and resource allocation process.

There are two primary research foci that have guided this effort. The first focus is intended to extend our prior use of feedback to influence regulation by examining its impact on *dynamic* resource allocation and, in particular, how feedback characteristics in combination with a meta-cognitive prime may enhance resource allocation processes with effects on situation assessment, strategy selection, and performance adaptation. As we noted in the introduction, resource allocation is a potential mechanism to account for adaptation to unexpected environmental perturbations. Our prior research did not address performance adaptation, thus, it is a logical extension of the research program. The second focus is intended to build a foundation for

extending our research paradigm such that it can better unpack the dynamics of the resource allocation process. Figure 1 illustrates the core resource allocation elements for the individual and team feedback loops: *goals* serving as references standards, *effort* allocation toward the respective loops, *performance* conveyed by *feedback*, and the *comparison* between the standard and current performance that yields a *discrepancy* that influences *behavioral choice* influencing resource allocation toward the individual or the team loop. Although our prior work extrapolated this heuristic process to posit the multilevel model that we validated, the research did not directly examine the dynamic interplay among these core elements over time. We believe that modeling these dynamics over time will yield important insights that will enable us to improve human performance in complex task domains. In particular, this extension of our paradigm enables more precise modeling of the limits and wide variance of human performance for dynamic resource allocation. This serves as a basis for more accurate evaluation of experimental interventions designed to improve multiple goal regulation and performance adaptation. These research foci are illustrated in Figure 3 below.

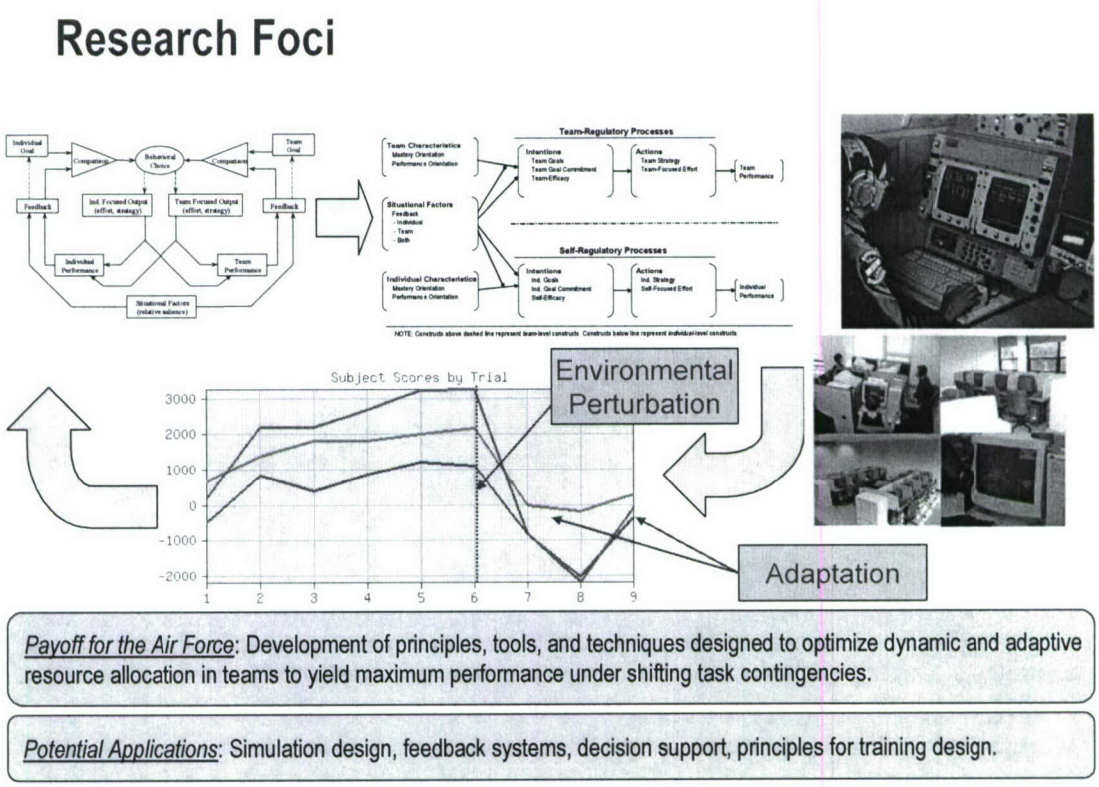


Figure 3. Dynamic Resource Allocation Research Foci.

Approach. We first adapted our team radar-tracking simulation that was used in the prior funding cycle to function as a generalized assignment task (e.g., Ross & Soland, 1975). As shown in Figure 4, TEAMSim is a PC-based, radar tracking simulation based on a cognitive task analysis that can be configured to emulate virtually any radar tracking task (e.g. AWACS; Kozlowski & DeShon, 2003). The simulation uses scripted events that unfold in real time, providing a shifting and emergent situation that demands adaptability. Individuals or three person teams are seated at simulated radar consoles that present multiple, dynamically interacting contacts. contacts possess different characteristics and threat profiles, and exhibit different patterns of movement. Participants (as individuals or interdependent teams) must make identification decisions and then render an overall decision for the contacts. In addition, complex task relations embedded in the scenario design necessitate shifts in task priorities and strategies, and in coordination requirements among team members. TEAMSim provides trainees with a dynamic, self-contained, and completely novel task environment that is appropriate for examination of complex skill acquisition and adaptation.

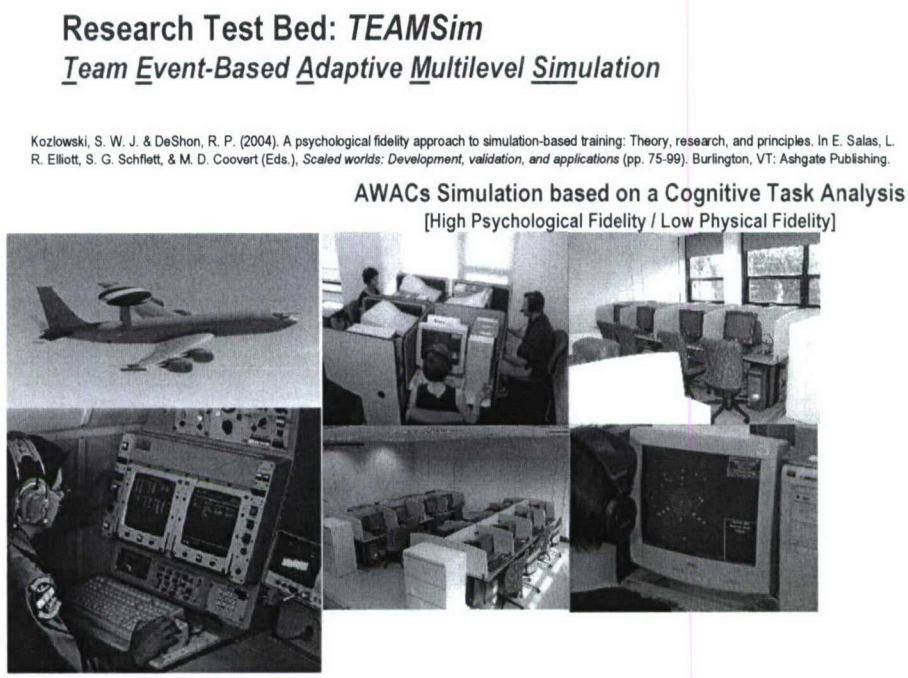


Figure 4. TEAMSim.

Our prior research configured TEAMSim to emulate 3 person teams of AWACS Weapons Directors. In that configuration, each team member had to dynamically allocate resources across the processing of individual and team contacts. Costs were incurred by either choice. If the individuals focused on team targets they incured costs associated with failing to process the individual targets. If team members focused on individual contacts they incured costs associated with failing to process team contacts. Performance could be maximized only through the efficient and balanced processing of both individual and team contacts. For the current research effort, we reconfigured TEAMSim to focus on individual resource allocation decisions that occur in team contexts. Participants were told that they were part of a virtual team and that they had both individual and team responsibilities; see Figure 5. By structuring the task in this way, we were able to focus on individual resource allocation decisions that occur in team contexts without the additional complexities of group dynamics.

Figure 5. TEAMSim Display Showing Individual (Yellow Squares) and Team (Blue Circles) Contacts.

Research Program Summary: Primary Studies

**Feedback Cycle Time and Environmental Change:
Effects on Situation Assessment, Resource Allocation, and Adaptation**

Individuals in a team work context have to continuously adapt their behaviors to maximize both individual and team-level performance. As team members strive for both individual and team goals, they have a limited amount of resources that are available at a given time. Thus, a choice must be made between two competing demands. Motivation and performance in teams, therefore, involve a multilevel, multiple-goal process of individual- and team-level regulation in which team members make decisions concerning the allocation of personal resources toward individual and team goals (See Figure 1). Through this multiple goal regulatory process, team members' resource allocation decisions are continuously updated and evaluated in a way that maximizes both individual and team performance. Therefore, successful adaptation in teamwork involves effective management of multiple goal self-regulatory processes such as monitoring performance discrepancies with respect to multiple goal states, and making appropriate resource allocation decisions.

In a self-regulation model for individual behaviors, feedback directs an individual's resource allocation decisions by providing knowledge of performance discrepancies with respect to current goal states (Carver & Scheier, 1998). In that sense, resource allocation as a dynamic process is regarded as one promising means to enhance situation assessment and diagnosis, strategy adjustment, and adaptation when a task environment shifts unexpectedly. What characteristics of feedback aid effective resource allocation? Although there is a considerable literature on performance feedback which concludes that feedback is essential to learning and performance, meta-analytic findings indicate that feedback has positive, null, and even negative effects (Kluger & DeNisi, 1996). We theorize that these differential effects for feedback are due to how well the feedback supports dynamic goal regulation and resource allocation.

In training settings, feedback or knowledge-of-results (KOR) is routinely provided after trainees have interacted with a to-be-learned task. Although this instructional practice fits with a heuristic model of the self-regulation process (i.e., goals set, goal striving behavior during practice, KOR and self-reflection on performance-goal discrepancies, strategy and effort revisions, and iterate the cycle), it fails to account for the dynamics of regulation and resource allocation. Indeed, we believe that this common form of feedback provision slows and delays the self-regulatory process, impedes resource allocation, and inhibits adaptation. One key inference from the multiple goal model is that the cycle time for feedback (i.e., the rate at which the feedback loop updates goal-performance discrepancy information), should be commensurate with the rate of change in the task environment. Such feedback should provide real-time updates to the regulatory loop, thereby enhancing situation assessment and diagnosis, strategy adjustment, and adaptation when a task environment shifts unexpectedly To the extent that feedback cycle time lags the rate at which task events – and especially unexpected environmental shifts – unfold, self-regulation and goal accomplishment will be impeded. Thus, we hypothesize that fast feedback updating that is commensurate with the task environment will be more effective in supporting self-regulation and resource allocation relative to KOR provided at the end of a practice episode. On the other hand, there is some very limited evidence which suggests that continuous feedback may be so salient that it would interfere with regulation and would thereby inhibit effective resource allocation (e.g., Chhokar & Wallin, 1984). Thus, it will also be important to evaluate the effects of fast feedback updating on regulation, resource allocation, and adaptation relative to a slower feedback cycle time.

This experiment also investigated the effects of environmental change on adaptation, given different rates of feedback cycle time and its effects on self-regulation and resource allocation. The literature on environmental change contrasts two different and ubiquitous types of change: (a) gradual or incremental change that moves off baseline for some period of time and then stabilizes as a new value or set of environmental relations and (b) abrupt or metamorphic change that shifts discontinuously from baseline to a new value or set of environmental relations (Tushman & Romanelli, 1985). Both types of change necessitate adaptation to the new values or set of relations or performance will be impeded. However, of the two types of change, abrupt shifts are likely to be more challenging because there is less time to detect and diagnose the change in environmental values. In contrast, gradual shifts afford more opportunity to detect a change in environmental values. Because the change is not constant, diagnosis may be difficult, but sufficient information to identify the aspect of the environment that is problematic may be possible such that adaptation is enhanced once change has concluded.

Thus, we hypothesized that participants would be better able to detect and diagnose the environmental shift under the gradual change condition relative to abrupt change and, as noted above, that feedback cycle time would facilitate this resource allocation adaptation. Thus, our focus is on how well participants diagnosed the environmental change via their feedback, adjusted their strategy, and adapted their resource allocation and performance.

Method

Participants. This experiment collected data from 281 undergraduate students recruited from psychology classes at a large mid-western university. Participants received extra-credit for their participation. Sixty-seven percent of the sample was female, and eighty-three percent was Caucasian. The majority of participants in the sample were between the ages of 18 and 22, with a mean of 20.

Procedure. Participants provided information on their ACT or GRE scores as measures of general cognitive ability via an online questionnaire prior to scheduling a lab session.

Upon arrival at the lab, participants received a brief training (approximately 15 minutes) on the simulation. To perform the simulation, participants had to hook contacts, query information about these contacts, and then make decisions based on collected information. After training, participants were given a chance to review the simulation manual for three minutes, and then perform in a four minute, unscored practice trial. Participants then completed nine trials of the task, each lasting four minutes and five seconds. Each trial was preceded by study time during which participants were given time (three minutes for the first three trials, one minute thereafter) to study the task manual. Each trial was also followed by feedback. Participants were given fifteen seconds to review their feedback for the previous trial. After receiving feedback participants also set overall score goals for the upcoming trial. The entire series of trials took approximately two hours to complete.

Simulation scenarios were designed to prompt learning and resource allocation. The simulation required participants to learn how to hook contacts, query information about these contacts, and then make decisions based on the information cues. In addition, contacts were distinguished as individual and team types, along with individual contacts belonging to the virtual teammate. Participants were instructed to only process those contacts that were their responsibility as an individual and a member of the team (i.e. individual and team contacts). This designation of contact type was signified visually via contact symbols; individual contact symbols were yellow squares whereas team contacts were symbolized by blue circles. Contacts appeared on the display in pairs that were distinguished as low and high priority via one of the information cues. Participants were told that high priority contacts were worth more points (but they were not informed about the point values). The display was also demarked by two perimeters, represented by concentric circles. Participants lost points when high priority contacts penetrated the perimeters, and lost additional points for every second a high priority contact remained unprocessed inside the perimeter.

Effective processing necessitated that participants monitor their entire airspace by zooming the range of their display to monitor activity on both perimeters, query contact priority, and prevent high priority contacts from penetrating the defensive perimeters. Note, however, that the strategies that would yield effective processing were not constant across the experiment. During early scenarios, low priority contacts were worth positive point values and so an effective strategy was to process ALL contacts as quickly as possible without allocating resources differentially. However, after the environmental change low priority contacts assumed negative point values. Thus, after the environmental change, differential resource allocation directed toward high priority contacts was necessary for effectiveness.

Experimental Design. The design was a fully crossed 3 (Feedback Type) by 2 (Environmental Change) with repeated measures across 9 trials. The first 3 trials constituted the skill acquisition phase, trials 4 to 6 constituted the change phase, and trials 7 through 9 constituted the adaptation phase.

Feedback Cycle Time Manipulation. Task events (contact pop-ups) occurred approximately every 10 seconds. Thus, fast and slow feedback cycle times were selected to bracket the rate of environmental events. Participants received one of three different types of feedback on all contacts: Fast Cycle Time (feedback scores updated every one second), Slow Cycle Time (feedback scores updated every 40 seconds), or End-of-Round (control: standard knowledge of results [KOR] provided after the trial had concluded). Feedback was displayed separately for team contacts and individual contacts.

Fast cycle time was expected to enhance situation assessment (detection of environmental change), strategy adjustment (a shift in relative resource allocation away from low priority contacts to more attention to processing high priority contacts), and performance adaptation (performance maintenance or reduced performance decrements) relative to end-of-round and slow cycle time. However, it was an open question as to whether rapidly cycling feedback might be too salient, distracting, and disruptive of resource allocation. Thus, the inclusion of the slow cycling condition.

Environmental Change Manipulation. Environmental change was induced by modifying the rules of the task, specifically the points given for correctly processing low priority contacts. During training, participants were instructed that high priority contacts were worth more points than low priority contacts. For the first three trials, processing a high priority contact resulted in a gain of 200 points, while processing a low priority contact resulted in a gain of 100 points. The value of high priority contacts was not altered, but the value of low priority contacts was altered in one of two ways. In the *abrupt change condition*, participants continued to receive 100 points for correctly processing low priority contacts through trials four, five, and six. However, the task rules changed abruptly in the seventh trial (and persisted through the eighth and ninth trials) such that processing low priority contacts (correct or incorrect) yielded -100 points. In the *gradual change condition*, participants incrementally lost points for processing low priority contacts during trials four, five, and six such that the point values were 50, 0, and -50, respectively. By trials seven, eight, and nine, participants received -100 points (equivalent to the abrupt change condition).

We expected that participants would be better able to detect and diagnose the environmental shift under the gradual change condition relative to abrupt change and, as noted above, that feedback cycle time would facilitate this resource allocation adaptation in terms of how well participants diagnosed the environmental change via their feedback, adjusted their strategy, and adapted their resource allocation and performance.

Measures

Cognitive Ability. Participants reported their ACT or SAT scores, which are proxy measures of general cognitive ability. The cognitive ability measure was created by standardizing ACT and SAT scores based on national norms. It was used as a covariate in all analyses.

Low Priority Contacts (LPC) Engaged. The number of LPC engaged was computed by summing the number of LPCs participants processed in each trial. For each trial, the maximum number of LPC engaged was 30. All participants were awarded 100 points for correctly processing LPCs in the first 3 trials. For participants in the gradual change condition, correctly processing LPCs was worth 50, 0, and -50 in trials 4, 5, and 6, respectively. For participants in the abrupt change condition, processing LPCs in trials 4, 5, and 6 remained at 100 points. For all participants, correctly processing LPCs in the last 3 trials was worth -100 points. For each trial and all participants, incorrectly processing LPCs was worth -100 points.

Total Priority Queries (TPQ). TPQ was computed by summing the number of times participants queried the priority level of each contact.

Engage Ratio. The engage ratio was computed by dividing the number of LPCs processed by the number of high priority contacts (HPC) processed for each trial (i.e., Engage Ratio = LPC/HPC). A smaller engage ratio indicates a more effective resource allocation toward high priority contact processing.

Performance. The total score for each trial was computed by summing the points awarded for LPC and HPC. For all participants and all trials, participants gained 200 points for correctly processing HPC and lost 200 points for incorrectly processing HPC. The points awarded for LPC was as described above.

Key Findings

Repeated Measures Multivariate Analyses of Covariance Variance (RM-MANCOVA) were used to evaluate the hypotheses. Experimental factors included: feedback cycle time (fast, slow, EOR) and environmental change (gradual and abrupt). Because our interest is on resource allocation and adaptation, analyses only examined differences for the last three trials, post-environmental change. Key dependent variables (DV) included priority queries, low priority contacts (LPC) engaged, the ratio of low priority contacts engaged to high priority contacts (HPC) engaged and performance (individual and team contacts) score. The number of LPC engaged is indicative of *situation assessment*, that is, whether participants have diagnosed a shift in the environment that makes processing of low priority contacts costly. Priority queries is indicative of selecting the appropriate *task strategy* to enable differential resource allocation, that is, whether participants queried the priority cue so as to distinguish types of contacts. The ratio of LPC/HPC represents relative resource allocation such that lower values are indicative of more appropriate resource allocations to high priority contact processing. Findings for these variables are discussed below.

DV: Number of Low Priority Contacts Engaged (Last 3 Trials). There is a main effect, $F(1, 274) = 14.42$, $p < .01$, of environmental change (EC) such that those who experienced gradual environmental change ($M = 14.81$, $SE = .78$) engaged fewer low priority contacts than those who experienced abrupt environmental change ($M = 19.01$, $SE = .78$). This indicates that those who experienced gradual change were able to diagnose and adapt to the change better than those who experienced abrupt change, as processing low priority targets is dysfunctional after the change for reasons outlined previously. Furthermore, there is a time by feedback cycle time interaction, $F(4, 548) = 2.45$, $p = .05$, such that those who receive fast feedback process fewer low priority contacts over time than those who receive only end of trial feedback, also consistent with this interpretation. Both findings support our hypotheses. The interaction is illustrated in Figure 1.1.

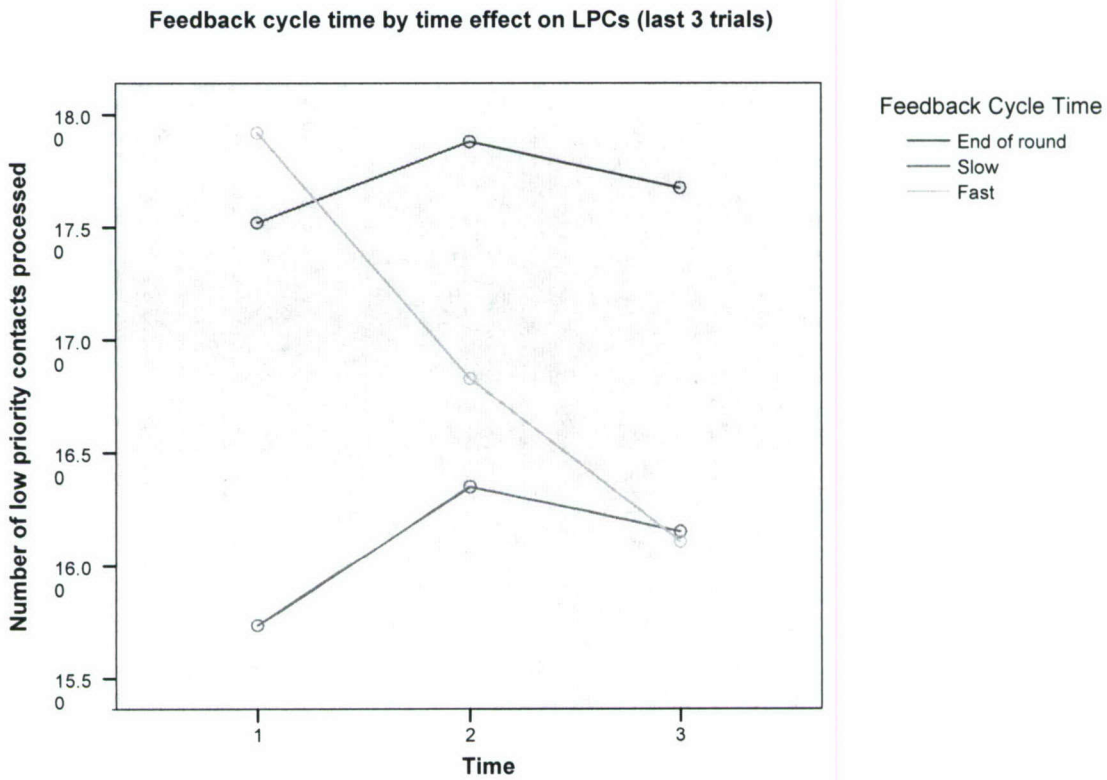


Figure 1.1

DV: Total Number of Priority Queries (Last 3 Trials). In order to execute the appropriate strategy of processing fewer low priority contacts, participants have to be able to distinguish contacts that are low and high priority. This is accomplished by querying the priority cue and then engaging the appropriate contact. It should be noted again that prior to the environmental change, the most effective strategy was to engage all contacts as quickly as possible, thus ignoring priority. Conversely, after the environmental change processing low priority contacts became costly, and a functional strategy of processing only high priority contacts required querying priority as a means of differentiating high and low priority contacts. Thus, the number of priority queries is a critical means of appropriate strategy adaptation and execution post change.

There is a main effect, $F(1, 274) = 4.51$, $p = .04$, of environmental change such that those who experienced gradual environmental change ($M = 15.64$, $SE = 1.47$) queried more than those who experienced abrupt environmental change ($M = 11.21$, $SE = 1.48$). This is also consistent with the above findings regarding differential processing of targets for those who experienced gradual environmental change. Querying more frequently permitted more appropriate resource allocation and was an effective strategy in the last three trials.

DV: Engagement Ratio (Last 3 Trials). In addition to processing fewer low priority contacts and querying priority more frequently, having a lower ratio of low priority contact engagement to high priority contact engagement was indicative of effective resource allocation. During the last three trials, the most effective resource allocation strategy was to engage only high priority contacts. A lower ratio indicates means that resource allocation was more focused on high priority contacts

There is a main effect, $F(1, 272) = 13.77$, $p < .01$, of environmental change such that ratio of low priority contacts engaged to high priority contacts engaged was smaller for those who experienced gradual environmental change ($M = 1.03$, $SE = .05$) relative to those who experienced abrupt environmental change ($M = 1.29$, $SE = .05$). There is also a time by feedback cycle time interaction, $F(4, 544) = 2.54$, $p = .04$, such that those who received fast cycling feedback have a ratio that decreases over time—indicating an appropriate shift in resource allocation—while those who receive only end of trial feedback have a stable ratio over time. Those who receive slow cycling feedback have an increasing ratio, indicating a non-optimal strategy. Both findings support our hypotheses. The time by feedback interaction is shown in Figure 1.2.

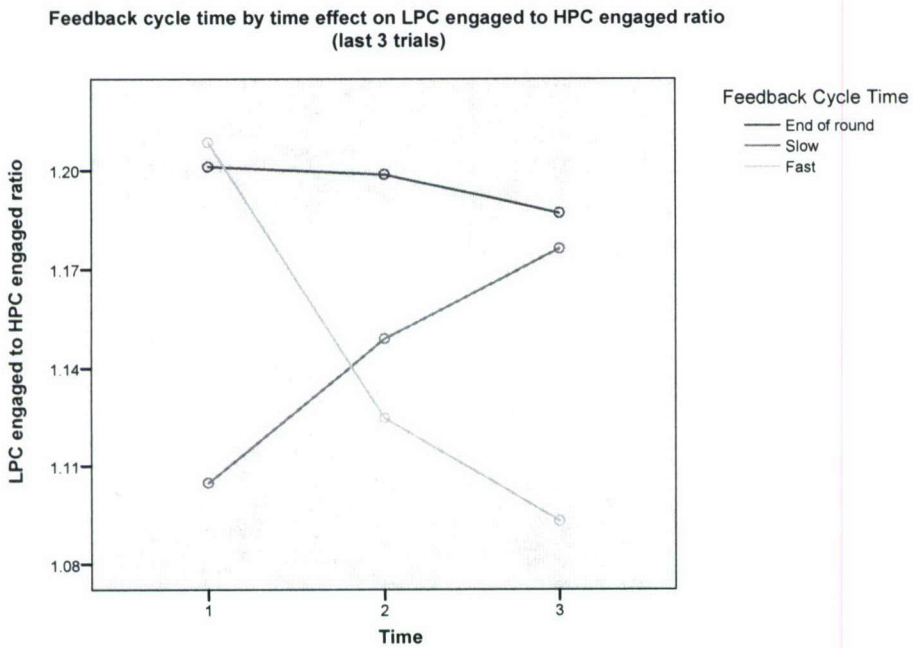


Figure 1.2

DV: Performance (Last 3 Trials). There is a main effect, $\gamma = -608.92$, $t(829.76) = -6.61$, $p < .01$, of the ratio of low priority engagement to high priority engagement controlling for cognitive ability, time, and condition such that individuals with a lower ratio performed better. This shows that differential resource allocation across these targets results in differing patterns of performance scores such that those participants who processed more high priority contacts relative to low priority contacts performed more effectively on the task. This is consistent with our hypotheses.

Discussion

The pattern of findings reported previously was consistent with our hypotheses. Gradual environmental change enable trainees to better diagnose and adapt, as expected. However, there is little that can be done to influence the nature of environmental change. Thus, beyond confirming the differential difficulties presented by different forms of environmental change, there are no substantial implications for training or system design. On the other hand, feedback cycle time, or the rate at which a system updates its state relative to the environment and regulatory goals, is a feature that can be controlled via technology design. More rapid feedback cycle times enabled trainees to more effectively assess the changing and changed environmental situation and to diagnose the need to process fewer low priority contacts, an effect that strengthened over time. Participants receiving rapidly updating feedback also showed a more appropriate relative resource allocation—again, an effect that strengthened over time. And, the more appropriate resource allocation predicted superior performance. In contrast, conventional KOR or end-of-round feedback was least effective. In addition, although there was some concern that rapidly updating feedback might be distracting or overwhelming, there was no evidence of detrimental effects. Indeed, compared to slower feedback updates, fast feedback yielded superior resource allocation (Figure 1.2), as those receiving slow feedback evidenced increasingly inappropriate resource allocation over time following environmental change.

Although these findings provide good support for the use of rapid feedback updates to support self-regulation, resource allocation, and adaptation, there are two primary limitations that are examined in a subsequent experiment. First, the number of trials available for adaptation to be tracked (the last 3 trials) was relatively brief. Thus, an extension of the design was needed to lengthen the period of time for adaptation, particularly for participants in the abrupt change condition. Second, training design research has demonstrated that a variety of interventions which prompt active monitoring of regulatory processes can improve learning and adaptation. Thus, an extension was needed to couple feedback cycle time with a manipulation that influenced trainee meta-cognition.

Meta-Cognition, Feedback Cycle Time, and Environmental Change: Effects on Self-Regulation, Resource Allocation, and Adaptation

Recent theory (Bell & Kozlowski, in press) and research (Bell & Kozlowski, in press) has posited and demonstrated that there are three primary psychological pathways – cognitive, motivational, and affective – for enhancing self-regulatory processes, learning, and performance adaptation. Of these, the cognitive pathway is most potent. Among the many interventions that may stimulate this pathway, prompting metacognition is very promising (Kozlowski et al., 2001; Smith, Ford, & Kozlowski, 1997). Metacognition has been described as planning, monitoring, and revising goal appropriate behavior (Brown, Bransford, Ferrara, & Campione, 1983). In other words, metacognition is an active awareness of the process of goal regulation as represented in the multiple goal model (Figure 1). For example, Meloth (1990) found that specific instruction on knowledge of cognition led to an increase of participants' metacognition. This increase was related to better strategy use and increased comprehension performance. Students who were taught metacognitive strategies performed better in class and were better able to transfer knowledge when faced with novel problems (Volet, 1991). Schmitt and Ford (2003) found that when trainees engaged in more metacognitive activity, they demonstrated better declarative knowledge, increased training performance, and higher self-efficacy after controlling for both ability and previous experience. Thus, we hypothesized that participants who received metacognitive inductions, that is, who were prompted to self-monitor their behavior during practice trials, to gauge the effectiveness of their strategies from feedback, and to explore ways that they could improve their performance wwould engage in more effective self-regulation, resource allocation, and adaptation. In addition, we hypothesized that metacogitive inductions would interact with feedback cycle time such that metacognitive inductions would enhance the positive effects of more rapid feedback updating observed in the prior experiment.

Method

Participants. This experiment collected data from 577 undergraduate students recruited from psychology classes at a large mid-western university. Participants received extra-credit for their participation. Sixty-two percent of the sample was female, and seventy-two percent was Caucasian. The majority of participants in the sample were between the ages of 18 and 22, with a mean of 20.

Procedure. Participants provided information on their ACT or GRE scores as measures of general cognitive ability via an online questionnaire prior to scheduling a lab session.

Upon arrival at the lab, participants received a brief training (approximately 15 minutes) on the simulation. To perform the simulation, participants had to hook contacts, query information about these contacts, and then make decisions based on collected information. After training, participants were given a chance to review the simulation manual for three minutes, and then perform in a four minute, unscored practice trial. Participants then completed nine trials of the task, each lasting four minutes and five seconds. Each trial was preceded by study time during which participants were given time (three minutes for the first three trials, one minute thereafter) to study the task manual. Each trial was also followed by feedback. Participants were given fifteen seconds to review their feedback for the previous trial. After receiving feedback participants also set overall score goals for the upcoming trial. The entire series of trials took approximately two hours to complete.

Simulation scenarios were designed to prompt learning and resource allocation. The simulation required participants to learn how to hook contacts, query information about these contacts, and then make decisions based on the information cues. In addition, contacts were distinguished as individual and team types, along with individual contacts belonging to the virtual teammate. Participants were instructed to only process those contacts that were their responsibility as an individual and a member of the team (i.e. individual and team contacts). This designation of contact type was signified visually via contact symbols; individual contact symbols were yellow squares whereas team contacts were symbolized by blue circles. Contacts appeared on the display in pairs that were distinguished as low and high priority via one of the information cues. Participants were told that high priority contacts were worth more points (but they were not informed about the point values). The display was also demarked by two perimeters, represented by concentric circles. Participants lost points when high priority contacts penetrated the perimeters, and lost additional points for every second a high priority contact remained unprocessed inside the perimeter.

Effective processing necessitated that participants monitor their entire airspace by zooming the range of their display to monitor activity on both perimeters, query contact priority, and prevent high priority contacts from penetrating the defensive perimeters. Note, however, that the strategies that would yield effective processing were not constant across the experiment. During early scenarios, low priority contacts were worth positive point values and so an effective strategy was to process ALL contacts as quickly as possible without allocating resources differentially. However, after the environmental change low priority contacts assumed negative point values. Thus, after the environmental change, differential resource allocation directed toward high priority contacts was necessary for effectiveness.

Experimental Design. The design was a fully crossed 2 (Metacognitive Prime) by 2 (Feedback Type) by 2 (Environmental Change) with repeated measures across 12 trials. The first 3 trials constituted the skill acquisition phase, trials 4 to 6 constituted the change phase, and trials 7 through 12 constituted the adaptation phase. Primary interest is on the adaptation phase, trials 7 to 12.

Metacognitive Induction Manipulation. Probe questions were developed to prime or induce metacognitive processing. The probes asked participants to what extent they were (a) monitoring their performance feedback, (b) evaluating the quality of their strategy, and (c) gauging the effectiveness of their resource allocation. The metacognitive induction was provided following the end of a trial (post-feedback) and before participants prepared for a subsequent trial.

The metacognitive induction was expected to enhance self-regulation, resource allocation, and adaptation.

Feedback Cycle Time Manipulation. Participants received one of two different types of feedback on all contacts: Fast Cycle Time (feedback scores updated every one second) or End-of-Round (control: standard knowledge of results [KOR] provided after the trial had concluded). Feedback was displayed separately for team contacts and individual contacts.

Fast cycle time was expected to enhance situation assessment (detection of environmental change), strategy adjustment (a shift in relative resource allocation away from low priority contacts to more attention to processing high priority contacts), and performance adaptation (performance maintenance or reduced performance decrements) relative to end-of-round feedback. In particular, fast feedback cycle time was expected to be especially beneficial under fast feedback updating.

Environmental Change Manipulation. Environmental change was induced by modifying the rules of the task, specifically the points given for correctly processing low priority contacts. During training, participants were instructed that high priority contacts were worth more points than low priority contacts. For the first three trials, processing a high priority contact resulted in a gain of 200 points, while processing a low priority contact resulted in a gain of 100 points. The value of high priority contacts was not altered, but the value of low priority contacts was altered in one of two ways. In the *abrupt change condition*, participants continued to receive 100 points for correctly processing low priority contacts through trials four, five, and six. However, the task rules changed abruptly in the seventh trial (and persisted through the trial 12) such that processing low priority contacts (correct or incorrect) yielded -100 points. In the *gradual change condition*, participants incrementally lost points for processing low priority contacts during trials four, five, and six such that the point values were 50, 0, and -50, respectively. In trials seven to twelve, participants received -100 points (equivalent to the abrupt change condition).

We expected that participants would be better able to detect and diagnose the environmental shift under the gradual change condition relative to abrupt change and, as noted above, that meta-cognitive primes and feedback cycle time would facilitate this resource allocation adaptation. Thus, our focus will be on how well participants diagnosed the environmental change via their feedback, adjusted their strategy, and adapted their resource allocation and performance.

<u>*Measures*</u>

Cognitive Ability. Participants reported their ACT or SAT scores, which are proxy measures of general cognitive ability. The cognitive ability measure was created by standardizing ACT and SAT scores based on national norms. It was used as a covariate in all analyses.

Cognitive Disengagement. Participants indicated whether or not they had stopped striving to perform the simulation. This variable was dummy coded as 1 to indicate disengagement and 0 for not disengaging. It was used as a covariate in all analyses.

Low Priority Contacts (LPC) Engaged. The number of LPC engaged was computed by summing the number of LPCs participants processed in each trial. For each trial, the maximum number of LPC engaged was 30. All participants were awarded 100 points for correctly processing LPCs in the first 3 trials. For participants in the gradual change condition, correctly processing LPCs was worth 50, 0, and -50 in trials 4, 5, and 6, respectively. For participants in the abrupt change condition, processing LPCs in trials 4, 5, and 6 remained at 100 points. For all participants, correctly processing LPCs in the last 3 trials was worth -100 points. For each trial and all participants, incorrectly processing LPCs was worth -100 points.

Total Priority Queries (TPQ). TPQ was computed by summing the number of times participants queried the priority level of each contact.

Engage Ratio. The engage ratio was computed by dividing the number of LPCs processed by the number of high priority contacts (HPC) processed for each trial (i.e., Engage Ratio = LPC/HPC). A smaller engage ratio indicates a more effective resource allocation toward high priority contact processing.

Performance. The total score for each trial was computed by summing the points awarded for LPC and HPC. For all participants and all trials, participants gained 200 points for correctly processing HPC and lost 200 points for incorrectly processing HPC. The points awarded for LPC was as described above.

Key Findings

RM-MANCOVA was used to evaluate the hypotheses. Experimental factors included: metacognitive primes (yes, no), feedback cycle time (fast, EOR) and environmental change (gradual, abrupt). Because our interest is on resource allocation and adaptation, analyses only examined differences for the last six trials, post-environmental change. Key DVs included priority queries, low priority contacts engaged, the ratio of low priority contacts engaged to high priority contacts engaged and performance (individual and team contacts) score. The number of LPCs engaged is indicative of *situation assessment*, that is, whether participants have diagnosed a shift in the environment that makes processing of low priority contacts costly. Priority queries is indicative of selecting the appropriate *task strategy* to enable differential resource allocation, that is, whether participants queried the priority cue so as to distinguish types of contacts. The ratio of LPC/HPC represents relative resource allocation such that lower values are indicative of more appropriate resource allocations to high priority contact processing. Findings for these variables are discussed below.

DV: Number of Low Priority Contacts Engaged (Last 6 Trials). As outlined in the previous study, the processing of low priority contacts is indicative of functional and dysfunctional strategies at different time points in the study. Initially, low priority contacts provide a small number of positive points. After environmental change these contacts provide only negative points, and thus resource allocation should shift toward HPC processing. A number of means of detecting situational awareness, strategy shift, and differential resource allocation are examined.

Consistent with our hypothesis, there is a main effect, $F(1, 509) = 11.18$, $p < .01$, for the metacognitive induction (MI) such that those participants who received the induction ($M = 16.35$, $SE = .47$) had better diagnosed the changed situation by engaging fewer LPCs than those without the induction ($M = 18.77$, $SE = .55$). Also consistent with our hypotheses, there is a feedback cycle time (FCT) by environmental change (EC) interaction, $F(1, 509) = 5.65$, $p = .02$, such that on average those participants who received fast feedback under gradual environmental change engaged the fewest low priority contacts. Thus, on average the gradual change, fast feedback condition yielded better adaptation via the reduced engagement of low priority contacts following the stabilization of the environmental change. There were no significant effects for the abrupt change condition. The interaction is Figure 2.1.

Interaction effect of FCT by EC on processing of LPCs (last six trials)

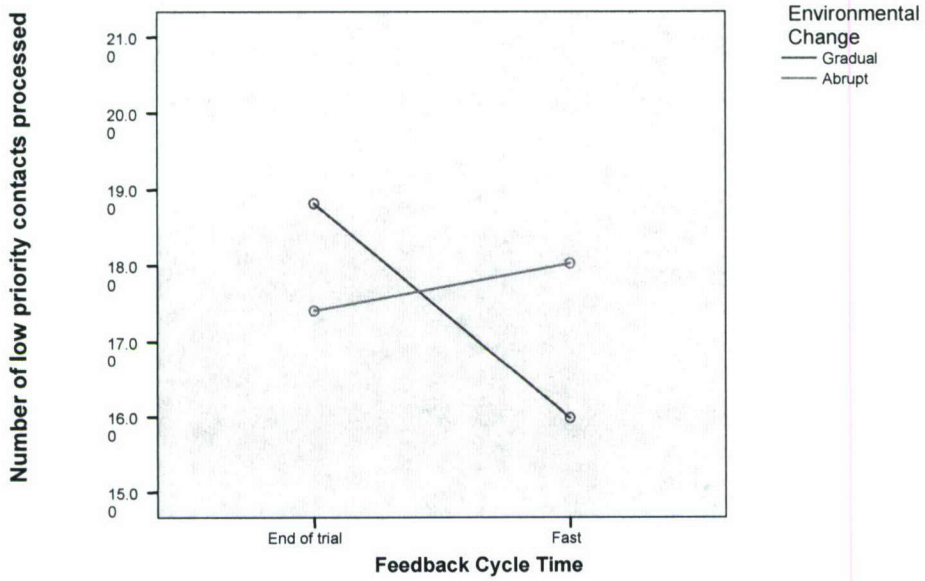


Figure 2.1

There is also a time by feedback cycle time interaction, $F(5, 2545) = 2.53$, $p = .03$, such that participants receiving fast feedback engaged fewer low priority contacts than those who received end of trial feedback. This difference increased across the six post-change trials of the experiment, indicating that those receiving fast FCT continued to improve their application of the appropriate task strategy as shown in Figure 2.2.

FCT condition by time interaction on processing of LPCs (last six trials)

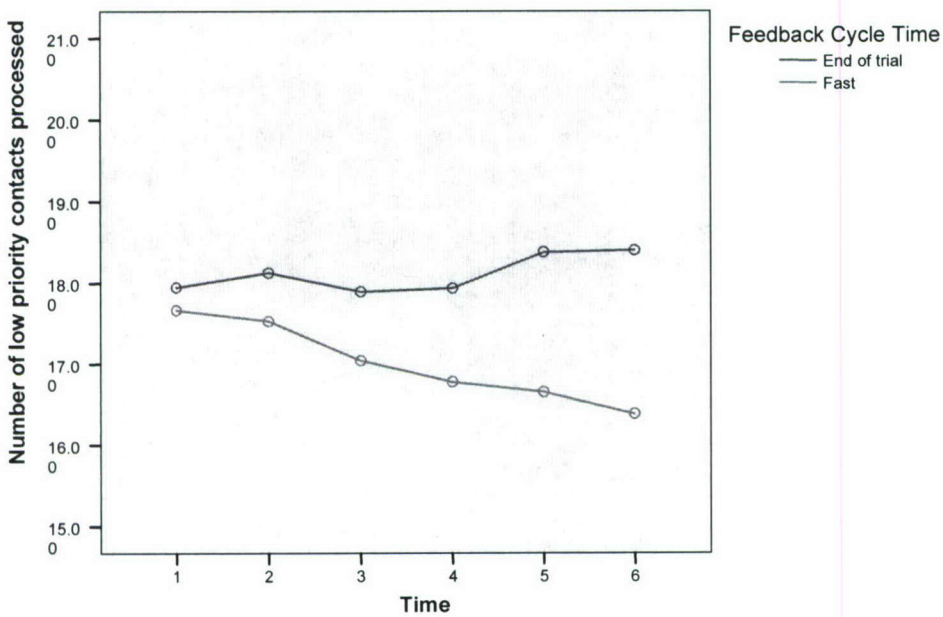


Figure 2.2

There is also a three way interaction, $F(5, 2545) = 3.32$, $p = .01$, of time by feedback cycle time by metacognitive induction such that those participants with no metacognitive induction and fast cycling feedback engaged progressively fewer low priority contacts over time relative to those given end of trial feedback; an adaptive behavior. Those participants who received the metacognitive induction showed an overall advantage for fast cycling feedback relative to those receiving end of trial feedback, but the effect was relatively constant over time. Figures 2.3 and 2.4 illustrate these effects.

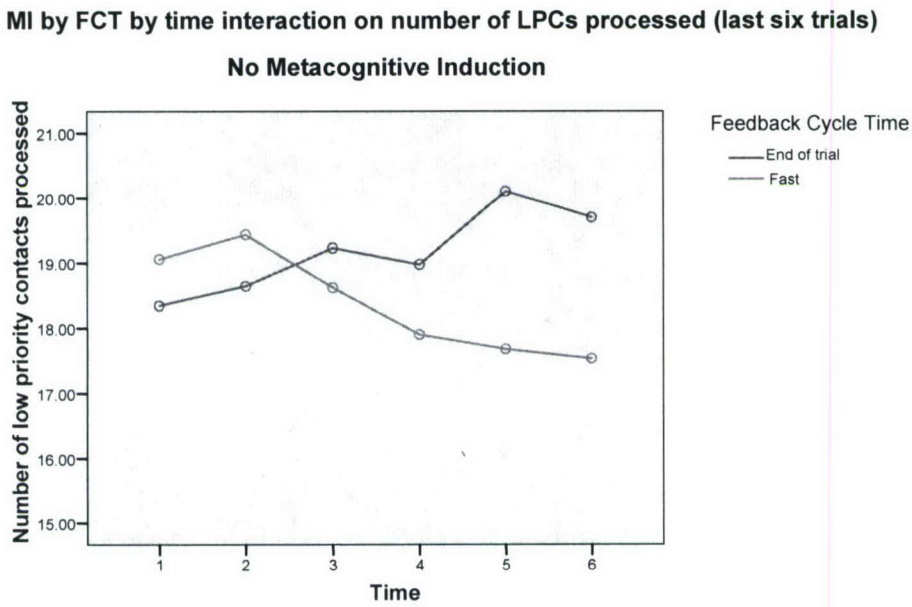


Figure 2.3

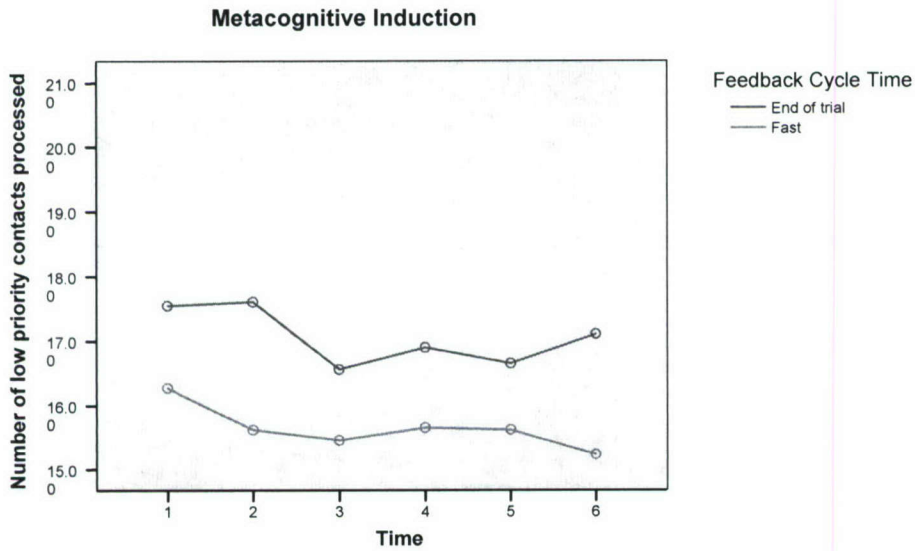


Figure 2.4

Thus, the metacognitive induction was effective at facilitating adaptation to change in the environment. Those without the metacognitive induction and receiving end of trial feedback increasingly processed low priority contacts; a strategy that was dysfunctional. Those without the metacognitive induction but receiving fast cycling feedback decreased their processing of LPCs over time, appropriately. However, the metacognitive induction offered a general benefit for those participants receiving fast cycling feedback, but there were no apparent changes over time. Conventional outcome (end of trial) feedback and "natural" self-regulation (no metacognitive induction) yielded the least effective adaptation.

There is also a three-way interaction, $F(5, 2545) = 2.52$, $p = .03$, of time by environmental change by metacognitive induction such that for participants without the metacognitive induction there is no meaningful difference in low priority contact processing across types of environmental change or time. However, for those participants receiving the metacognitive induction, there wsa an initial advantage under gradual environmental change relative to abrupt environmental change. This difference is likely due to the opportunity to use feedback diagnostically during the change phase under gradual change. This advantage diminished over time as the participants in each condition converged on the number of low priority contacts they processed. This interaction is depicted in Figures 2.5 and 2.6.

EC by MI by time interaction on number of LPCs processed (last six trials)

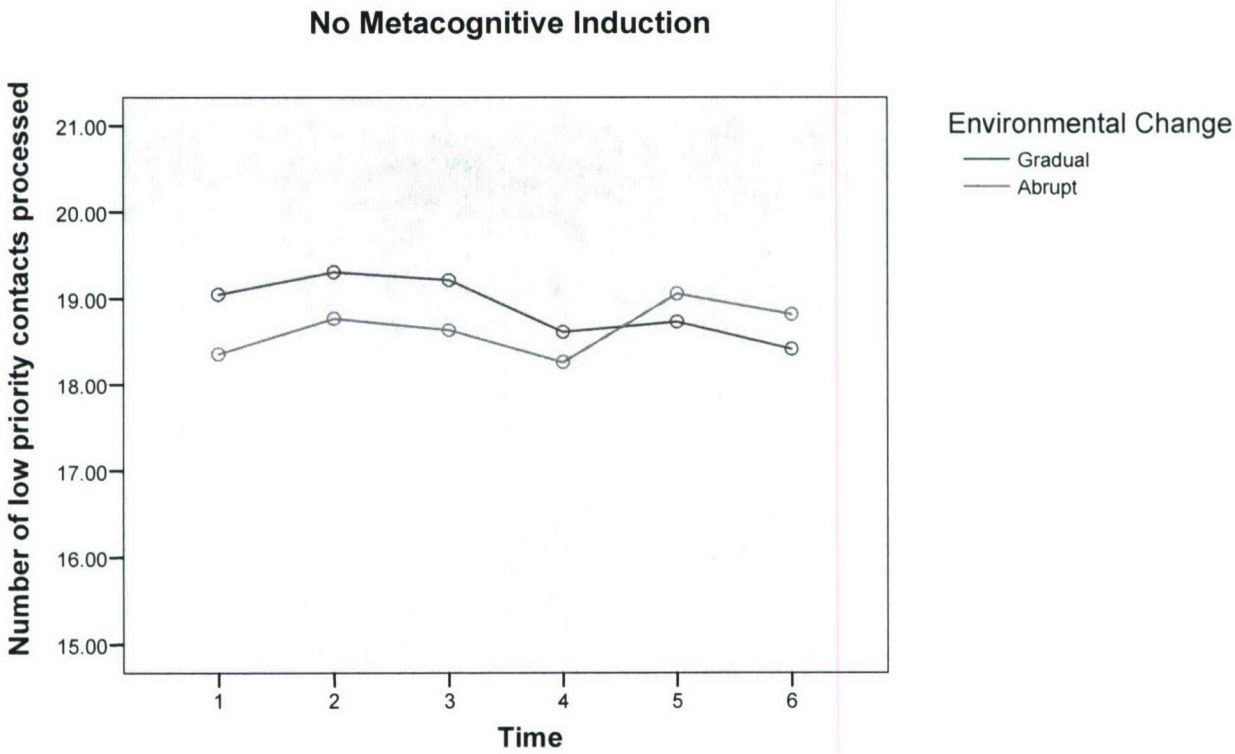


Figure 2.5

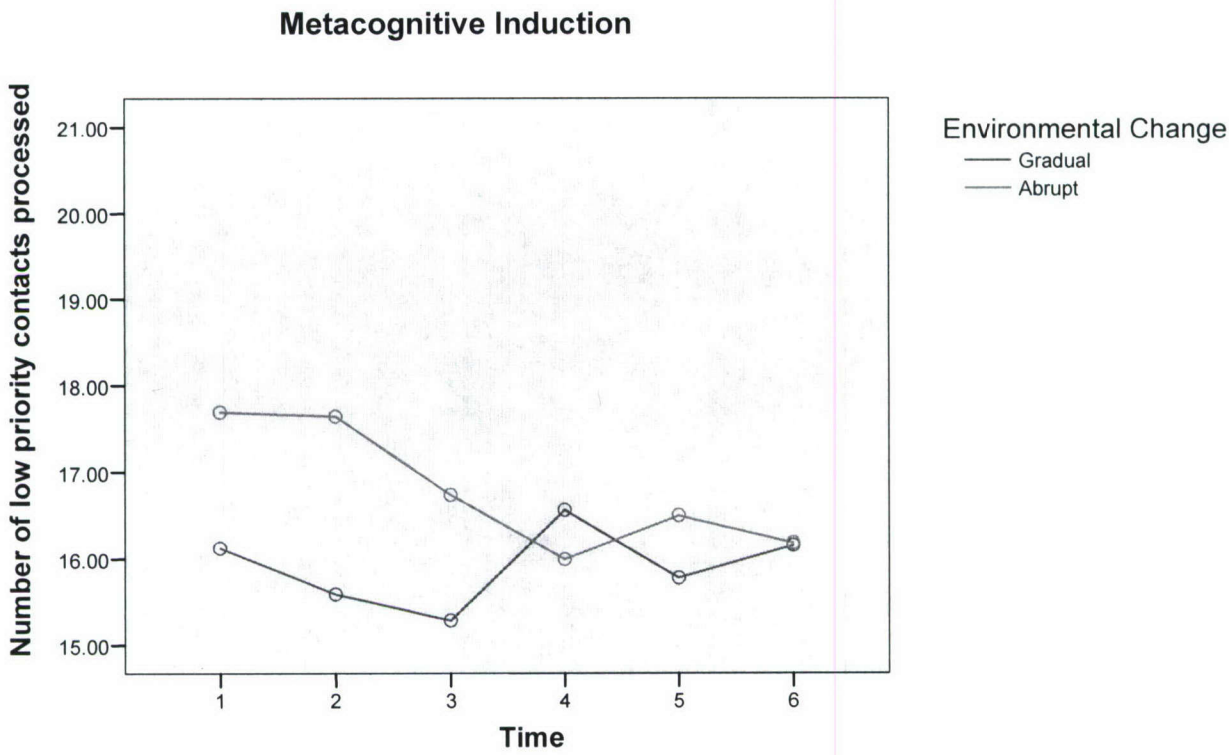


Figure 2.6

Thus, it can be seen that those participants given the metacognitive induction and experiencing gradual environmental change did the best initially in terms of finding the appropriate strategy of reduced low priority contact processing. However, those given the metacognitive induction and experiencing abrupt environmental change eventually converged to the same strategy. Thus, the metacognitive induction provided a robust improvement in adaptation regardless of the nature of environmental change.

DV: *Total Number of Priority Queries (Last 6 Trials).* As discussed earlier, in order to execute the appropriate strategy of processing fewer low priority contacts, participants have to be able to distinguish contacts that are low and high priority. This is accomplished by querying the priority cue and then engaging the appropriate contact. It should be noted that prior to the environmental change, the most effective strategy was to engage all contacts as quickly as possible and to ignore contact priority, whereas after the change processing low priority contacts became costly. Thus, the number of priority queries is a critical means of appropriate strategy adaptation and execution post change.

There is a main effect, $F(1, 509) = 3.76$, $p = .05$, of environmental change on contact priority querying (CPQ) in the last six trials such that those experiencing gradual change ($M = 10.56$, $SE = .84$) queried contact priority more than those experiencing abrupt change ($M = 8.23$, $SE = .86$). Another main effect, $F(1, 509) = 7.00$, $p = .01$, was found for the metacognitive induction in the last six trials such that those given the induction ($M = 10.99$, $SE = .78$) queried contact priority more than those without it ($M = 7.81$, $SE = .92$). Additionally, there was a time by feedback cycle time interaction, $F(5, 2545) = 3.98$, $p < .01$, in the last six trials such that those receiving fast cycling feedback queried contact priority more than those participants given end of trial feedback. This difference manifested primarily in the last two trials and is illustrated in Figure 2.7.

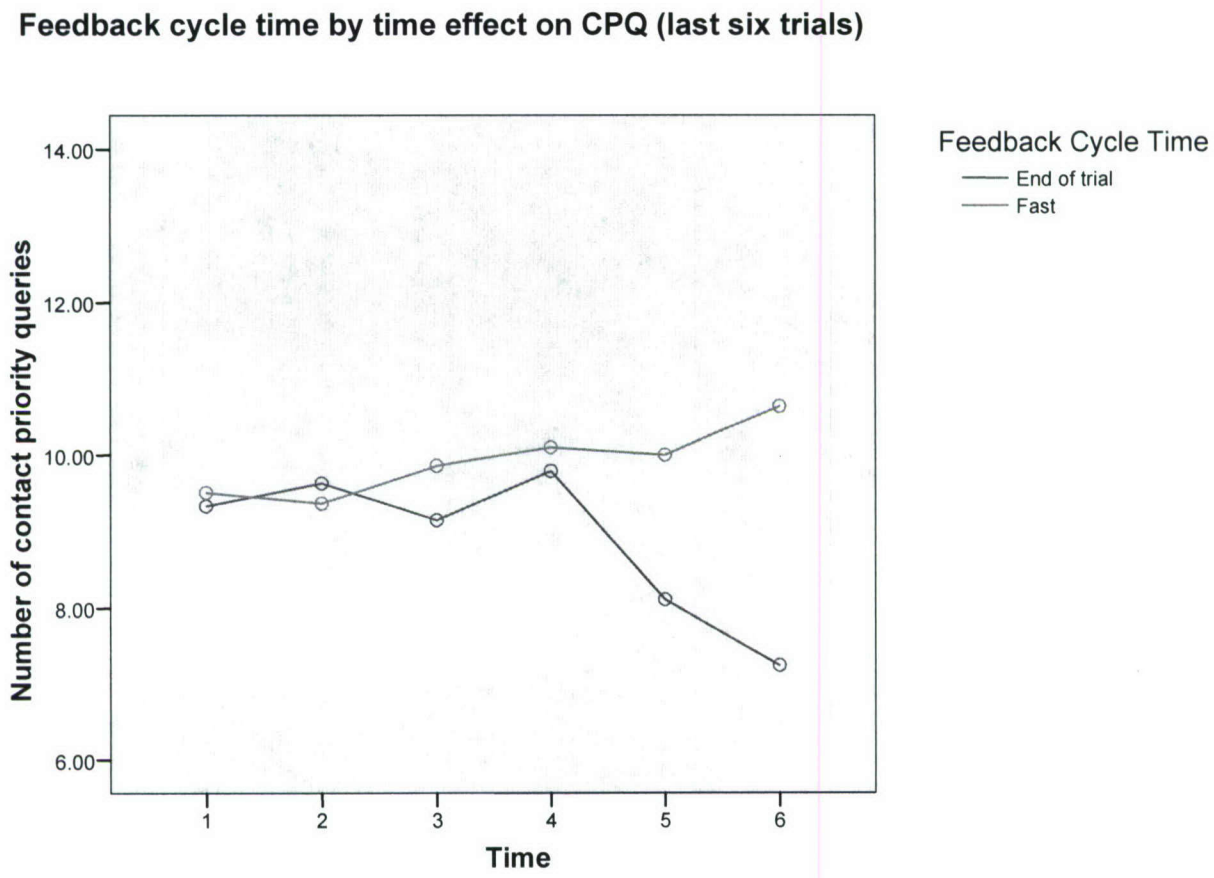


Figure 2.7

As noted previously, querying priority is an appropriate strategy for diagnosing how to appropriately allocate resources; that is choosing to engage high priority contacts and not processing low priority ones. As shown in the prior Figure, total contact priority querying indicates whether participants queried contact priority as a means to allocate resources to high priority contacts. This resource allocation represents an adaptive behavioral pattern. When feedback cycle time was fast, participants showed more total contact priority querying, indicating that they were better able to diagnose the environmental change relative to those given end of trial feedback, where a marked decrease in priority querying over time can be observed.

There is a time by environmental change by metacognitive induction interaction, $F(5, 2545) = 4.78$, $p < .01$, on contact priority querying in the last six trials such that those participants experiencing gradual environmental change queried more contact priorities than those experiencing abrupt environmental change, with the metacognitive induction shifting this effect. To expound on this finding, in the absence of the metacognitive induction there is no effect of environmental change over time. However, when participants were given the metacognitive induction, there was an initial advantage for those participants experiencing gradual change relative to those experiencing abrupt change. This is likely due to the opportunity to discover the change during the change phase, evidenced by the fact that those in the abrupt environmental change condition converge to the same levels of priority querying over time. This finding is illustrated in Figures 2.8 and 2.9.

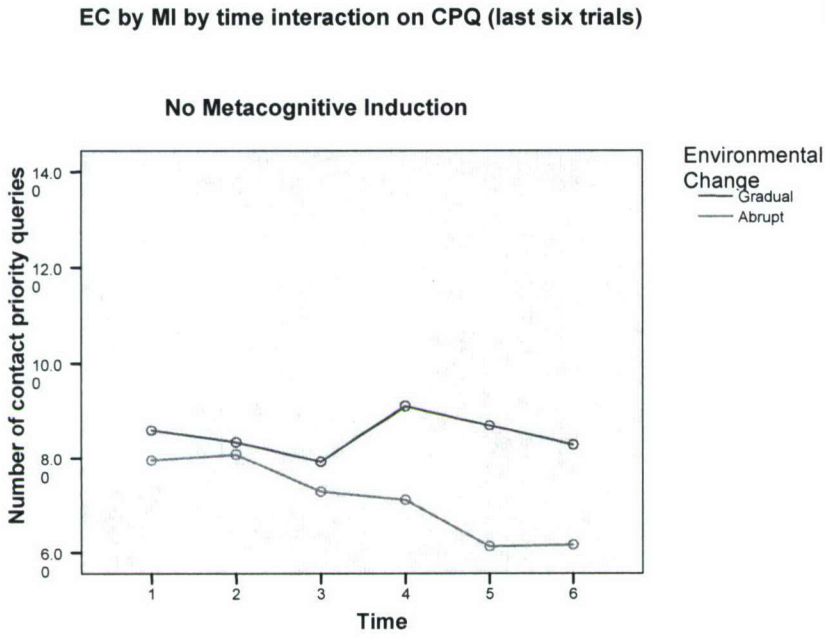


Figure 2.8

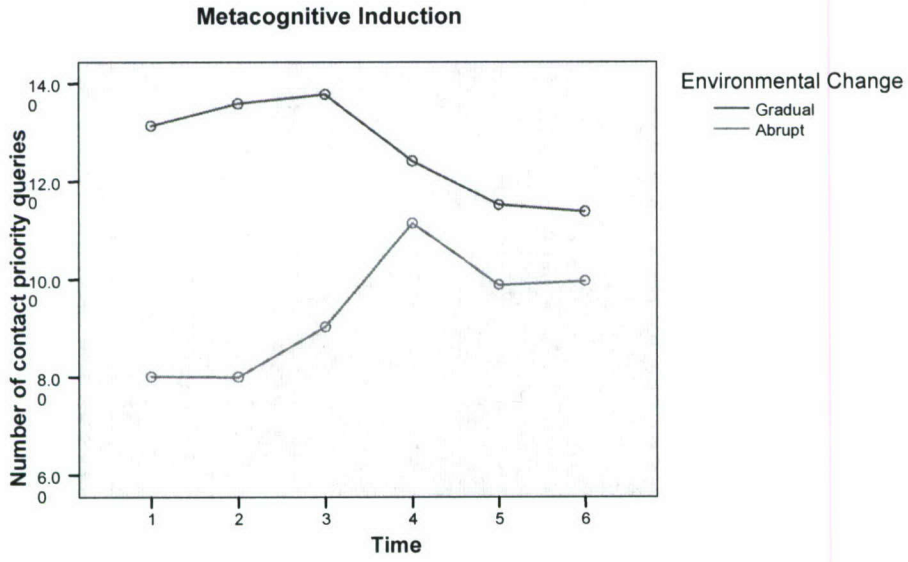


Figure 2.9

Thus, the metacognitive induction is an effective intervention to ameliorate the negative effects of environmental change on appropriate strategy selection and adaptive behavior; that is, using contact priority querying to appropriately allocate resources to high versus low priority contact engagements.

DV: *Ratio of Low Priority Contacts Engaged to High Priority Contacts Engaged.* In order to get more directly at the differential resource allocation noted above, we created a ratio of low to high priority contacts engaged such that smaller ratios indicate more optimal resource allocation. While participants should shift effort away from the processing of low priority contacts, they should also be focusing this effort toward the processing of high priority contacts.

There was a main effect, $F(1, 498) = 6.69$, $p = .01$, for the metacognitive induction on the ratio of LPC engaged to HPC engaged such that those participants who received the metacognitive induction ($M = 1.18$, $SE = .03$) had a smaller ratio, indicating appropriate resource allocation toward high priority contacts and away from low priority contacts as compared to those participants who had not received the induction ($M = 1.30$, $SE = .04$).

There was also a feedback cycle time by environmental change interaction, $F(1, 498) = 5.96$, $p = .02$, such that those given fast feedback and experiencing gradual change had the lowest ratios, thus showing the adaptive benefits of fast feedback for diagnosis when change was gradual (relative to abrupt). When feedback cycle time was fast and environmental change was gradual participants were able to effectively diagnose the appropriate strategy of allocating more resources to high priority contacts and thus curtail resource allocation to low priority contacts. This further suggests that participants in the remaining conditions failed to diagnose the appropriate strategy of allocating more resources to high priority contacts and away from low priority contacts. This finding is illustrated in Figure 2.10.

Environmental change by feedback cycle time interaction (over last six trials)

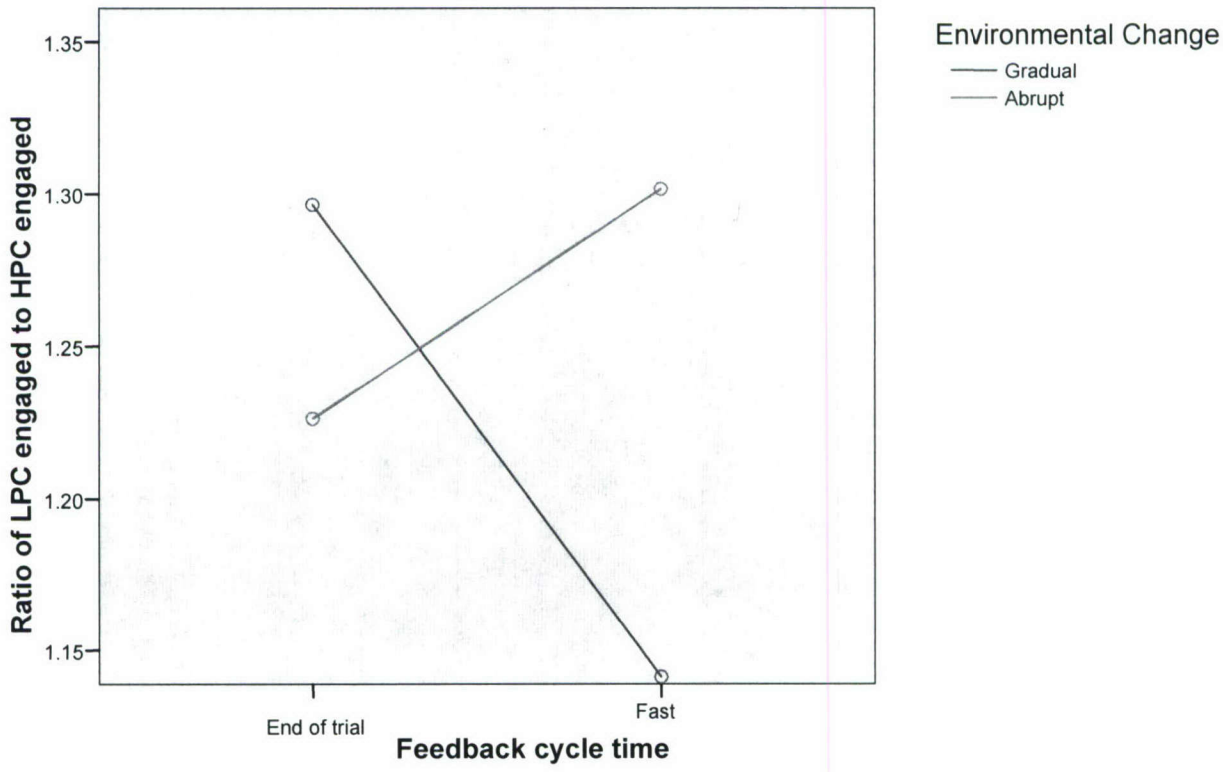


Figure 2.10

There is also an interaction, $F(5, 2490) = 3.43$, $p < .01$, of feedback cycle time by time on the ratio of LPC engaged to HPC engaged such that those receiving fast cycling feedback were better able to diagnose an appropriate resource allocation strategy to process more HPC and fewer LPC. Alternatively, those receiving only end of trial feedback increasingly followed a dysfunctional resource allocation strategy such that they processed more LPCs over time. This finding is illustrated in Figure 2.11.

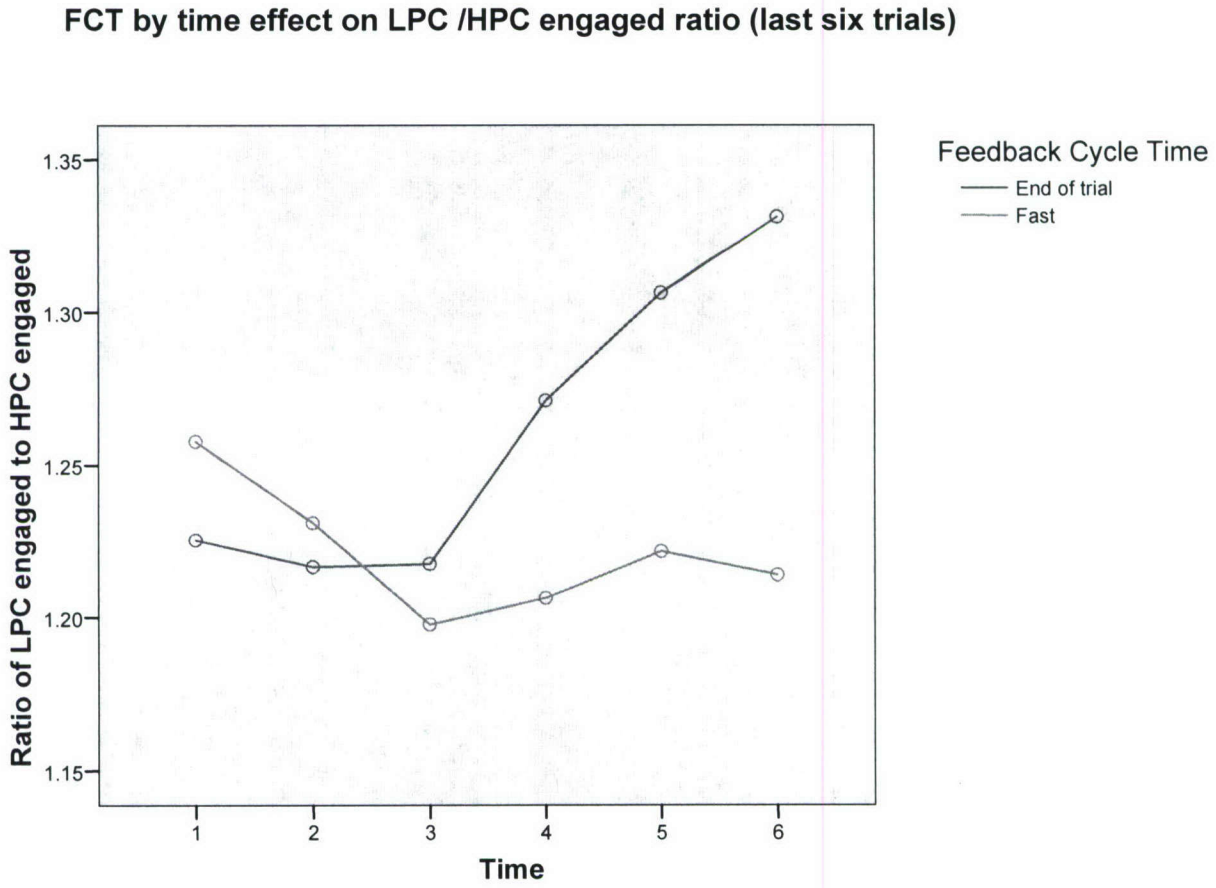


Figure 2.11

DV: Performance. It is important to demonstrate that appropriate resource allocation predicts performance. For last 6 trials, there is a main effect, $\gamma = -935.71$, $t(2900.99) = -17.38$, $p < .01$, for engage ratio on participant performance controlling for cognitive ability, cognitive disengagement, time, and condition. Thus, those participants who engaged in the appropriate resource allocation strategy by focusing on processing more high priority contacts relative to low priority contacts in the last six trials performed better.

Qualitative Analyses

In addition to the quantitative effects addressed previously, we also examined qualitative statements obtained from participants. After the experimental trials concluded, participants were asked whether they had detected an environmental change and the type of resource allocation strategy adaptation needed to cope with it. Those open-ended responses were coded into two categories to capture the qualitative expression of appropriate strategy (QEAS): those who deduced the strategy and those who did not.

There is an effect of QEAS by feedback cycle time on number of low priority targets engaged ($F(5, 2545) = 3.92$, $p < .05$) such that for those participants receiving only end of trial feedback, those who were able to express proper strategy processed fewer low priority contacts across the majority of trials relative to those

who failed to express the correct strategy. This contrasts to those participants in the fast cycling feedback condition. Of these participants, a difference in the number of low priority contacts processed between those who expressed the correct strategy and those who didn't does not appear until after the environmental change has occurred. This is shown in Figures 2.12 and 2.13.

QEAS by feedback cycle time effect on LPC processing (all twelve trials)

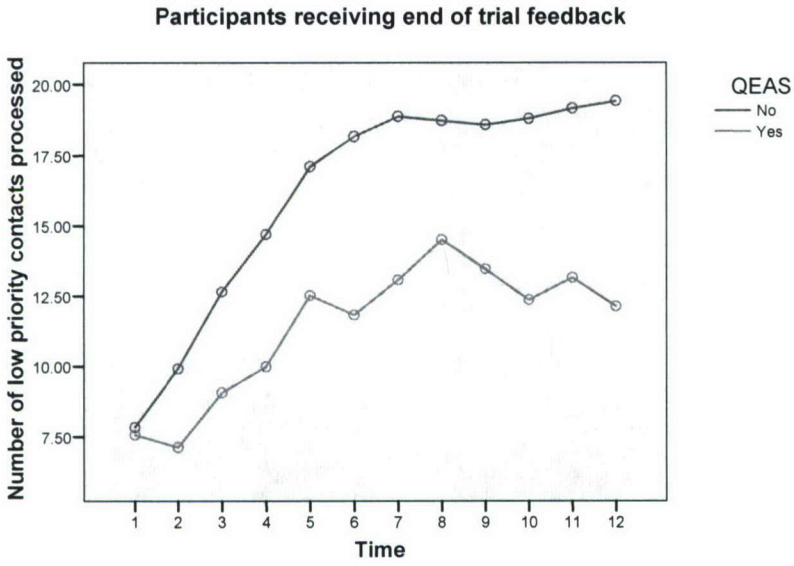


Figure 2.12

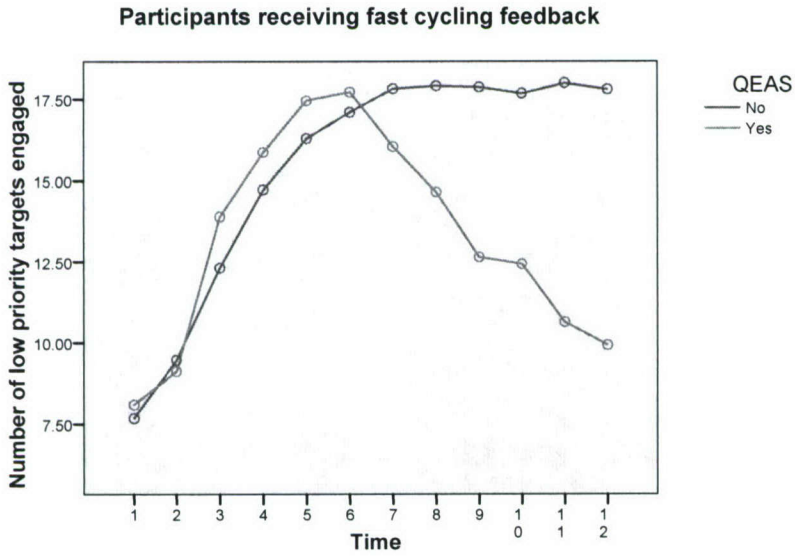


Figure 2.13

Recall that the processing of low priority contacts is only detrimental in the last six trials of the experiment and their processing in the first six trials (first three trials for those with gradual change) is an appropriate strategy. Thus, fast cycling feedback not only allowed participants to determine early in the experiment that querying was not useful and better scores could be achieved by processing everything, but it also allowed them to use feedback diagnostically later and to realize that they needed to query in order to increase scores after the environmental change.

This effect is further illustrated in a QEAS by feedback cycle time interaction on contact priority querying ($F(5, 2545) = 2.88$, $p < .01$). This effect is consistent with the above interaction such that for those participants who receive only end of trial feedback, those who eventually express the correct strategy qualitatively query more than those who don't express the correct strategy throughout the experiment – even pre-environmental change. Those given fast cycling feedback show no differences across QEAS for the trials pre-change, and the appropriate disjunction only occurs when the environmental change on the task forces them to adapt. This finding is shown in Figures 2.14 and 2.15.

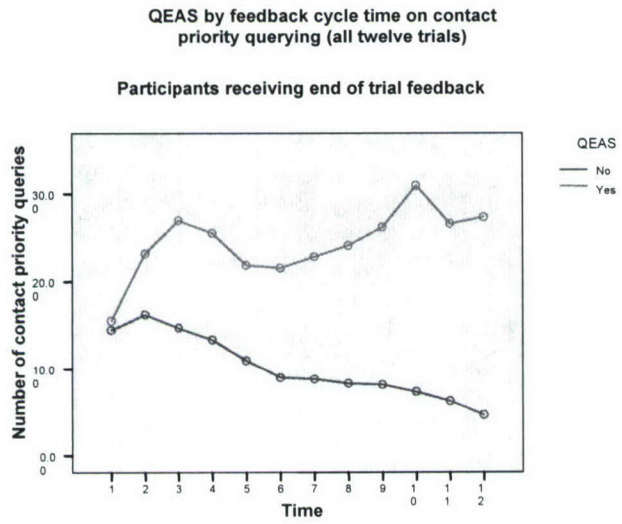


Figure 2.14

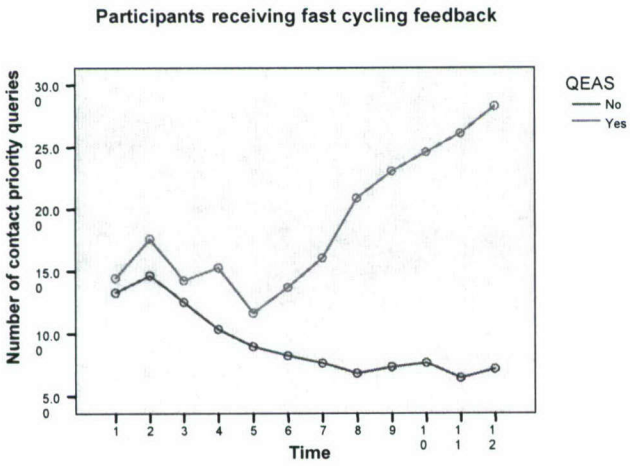


Figure 2.15

The implication of this finding is that those receiving fast cycling feedback are able to use the feedback diagnostically throughout the experiment to alter their strategy as the environment changed. Initially, all participants queried the priority of contacts, as this was stipulated in the instructions. Those participants who eventually uncovered the environmental change receiving fast feedback altered their strategy and queried less in order to process more targets (an optimal strategy pre-environmental change), and then again altered their strategy post change in order to query and distinguish high and low priority targets (an optimal strategy post-environmental change). Those participants who eventually uncovered the environmental change and received only end of trial feedback did not alter their behavior early in the experiment (to less querying of priorities) and thus were not performing at an optimal level during this time.

Discussion

The pattern of findings for experiment 2 essentially replicated the effects reported for experiment 1, and also extended the findings in important and useful ways. With respect to replication, we again showed that there was an adaptive advantage under gradual versus abrupt conditions of environmental change due to the greater opportunity to detect unstable aspects of the environment and to identify key aspects of the situation relevant to those changing conditions. Although this finding in and of itself is not important because the nature of environmental change is not malleable in the real world, what is important are its interactions with the substantive manipulations which represent training design (metacognitive intervention) and embedded decision supports (feedback cycle time); that is, features that can be used to augment the effectiveness of human operators in complex task environments. Fast feedback was again instrumental to adaptation, and particularly advantaged participants in the gradual change condition.

With respect to extension, the use of additional trials to observe adaptation and the addition of the metacognitive intervention to stimulate self-regulation yielded several interesting findings. First, the additional time to assess adaptation showed that those participants receiving fast cycling feedback adapted better over time in terms of indications of appropriate diagnosis of the situation, appropriate strategy selection, and more optimal resource allocation. In addition, the qualitative analyses that examined differences between those participants who deduced the appropriate strategy and those who did not revealed that those receiving fast feedback were able to better model the appropriate strategy across the experiment. That is, they used the most effective strategy early on during the skill acquisition phase (which was to process all contacts quickly), were able to detect better during the change phase, and were then able to adapt their strategy and resource allocations during the adaptation phase. In summary, fast cycling feedback evidenced several findings that make it a promising intervention for further experimental evaluation and, possibly, application development.

The metacognitive intervention also evidenced several promising findings. Those receiving the metacognitive induction showed advantages in situation assessment and appropriate strategy selection that were amplified under the gradual change condition. As above, we believe that gradual change afforded greater opportunities to detect and diagnose. Importantly, however, those receiving the metacognitive induction under abrupt change evidenced convergence with those under gradual change over time. This is an important finding because it shows that the metacognitive induction for self-regulation improved the ability of trainees to diagnose the nature of change and to better adapt even when the nature of change was metamorphic. We did not observe convergence for trainees who did not receive the metacognitive induction. Moreover, the metacognitive induction provided an overall advantage to those receiving fast cycling feedback in terms of appropriate strategy use, suggesting that these two design features combine well. In summary, consistent with the multiple goal regulation model, the metacognitive intervention demonstrated several positive effects on resource allocation and adaptation. It represents a promising intervention for further experimental evaluation and, possibly, application development. One notable thing to bear in mind is that the intervention is exceptionally easy to implement and can be deployed in a wide variety of training or performance devices. Thus, its potential applicability and impact is high.

Finally, although the research findings are quite promising, they also revealed a need to advance the paradigm. In particular, we advanced our ability to model the dynamics of adaptation to environmental change. However, the more specific micro dynamics (i.e., within person cycles of goals, effort, and performance) inherent in the multiple goal model remain elusive in the approach taken in experiments 1 and 2. Accordingly, the next step in our evolving program sought to extend our paradigm to enable more precise modeling of regulatory dynamics.

Multiple Goal Resource Allocation and Skill Acquisition:
Investigating the Dynamics of Self-Regulation

The purpose of this investigation is to better understand the dynamic process of regulating actions over time in response to performance feedback. Although literally hundreds of motivation models exist that specify dynamic regulatory processes, there are very few empirical investigation of process that actually model dynamics. This investigation serves as a launching point for the investigation of the dynamic processes that are implied in our regulatory model (e.g., DeShon et al., 2004). Although our focus is on the empirical evaluation of our model, the results of this investigation speak to virtually all models of motivation and self-regulation since these models share a common core set of variables and processes that are detailed next.

First, it is widely agreed that individuals possess desired states of being (i.e, goals). An individual's current state of being may be congruent with the desired state (e.g., hunger, thirst, breathing, health). Frequently, however, individuals possess desired states that are currently incongruent with the individual's actual state of being. In other words, individuals frequently want more or less of something than is represented in their current state of being such as such as pain, school grades, salary, leisure time, a bigger or nicer residence, respect, recognition, control, etc.... Second, individuals invest effort over time to maintain congruent goals or obtain incongruent goals. However, the invested effort is not uniform across tasks and goals. Individuals invest tremendous effort to achieve certain goals while investing relatively less effort in the pursuit of other goals. This empirical pattern of effort investments suggests that goal states differ along one or more dimensions. At a minimum is appears that goal states are readily differentiated along the two dimensions of importance and the anticipated effort required to obtain the goal state. Learning models address the development of these belief states. The goal importance and the effort believed to be required to achieve the goal state combine through a currently unknown function to yield the actual effort expended in the pursuit of a particular goal. Bandura (1989) cogently described this empirical pattern of human behavior as:

> *"People motivate and guide their actions through proactive control by setting themselves valued goals that create a state of disequilibrium and then mobilizing their abilities and effort on the basis of anticipatory estimations of what is required to reach the goals."*

Third, virtually all motivation models incorporate some form of an evaluative component that makes it possible for the individual to evaluate the effectiveness of the invested effort with respect to the goal. Is the new current state closer to the goal, farther away from the goal, or unchanged? The theoretical details of this process vary widely (e.g., comparators vs. efficacy beliefs) but empirically it appears that individuals actively monitor their environment for knowledge of results or feedback information that may be used to evaluate the effect of the invested effort. What happens at this point is the crucible for explanations of behavior.

Once the individual obtains information that is indicative of the new current state a many-degree-of-freedom problem is encountered. How will the individual respond to the information about the current state after the effort investment? At a minimum, the individual may revise the estimate of the effort required to achieve the goal upward or downward. The individual may revise the goal upward or downward. The individual may simultaneously revise both the goal and the effort estimate upward or downward independently. The individual may also decide to simply collect more information through continued effort expenditures and leave the goal and estimated effort unchanged.

Modeling the Dynamics of Motivation

The dynamic process of setting a goal, investing effort to maintain or obtain the goal, examining performance feedback to evaluate the success of the effort investment, revising the goal and/or the estimate of required effort investments for subsequent goal pursuits that, in turn, affect subsequent performance and feedback is widely discussed in the motivation literature. However, the current methods used to investigate this dynamic process may not adequately capture the expected dynamics. Two methods currently dominate motivational investigations. In fact, much more effort has been devoted to

developing models of behavior than to the empirical investigation of actual behavioral dynamics. The underlying thesis of our approach is that it may prove useful to lay aside theoretical debates for a short time and let the data speak a bit more loudly.

Vector autoregressive models (VAR) are a very common set of models used in the linear dynamic systems literature to capture system dynamics. A finite order, covariance stationary VAR model may be represented as,

$$A_0 y_t = A_1 y_{t-1} + \mathrm{L} + A_p y_{t-p} + u_t \qquad (1.1)$$

where $y_t = \left[y_{1t}, \mathrm{K}, y_{Kt}\right]'$ is a K-dimensional vector of observable variables, the A_i, $i = 0, 1, \mathrm{K}, p$, are (K x K) coefficient matrices and $u_t = \left[u_{1t}, \mathrm{K}, u_{Kt}\right]'$ is a white noise error process such that the u_t are temporally uncorrelated with zero mean and positive definite covariance matrix Σ_u. The modeled lag length, p, is termed the order of the VAR process and so the general representation of the model is VAR(p). As an example, a trivariate (K = 3) VAR(2) model may be represented in expanded form as,

$$\begin{pmatrix} a_{11}^0 & a_{12}^0 & a_{13}^0 \\ a_{21}^0 & a_{22}^0 & a_{23}^0 \\ a_{31}^0 & a_{32}^0 & a_{33}^0 \end{pmatrix} \begin{pmatrix} y_{1t} \\ y_{2t} \\ y_{3t} \end{pmatrix} = \begin{pmatrix} a_{11}^1 & a_{12}^1 & a_{13}^1 \\ a_{21}^1 & a_{22}^1 & a_{23}^1 \\ a_{31}^1 & a_{32}^1 & a_{33}^1 \end{pmatrix} \begin{pmatrix} y_{1t-1} \\ y_{2t-1} \\ y_{3t-1} \end{pmatrix} + \begin{pmatrix} a_{11}^2 & a_{12}^2 & a_{13}^2 \\ a_{21}^2 & a_{22}^2 & a_{23}^2 \\ a_{31}^2 & a_{32}^2 & a_{33}^2 \end{pmatrix} \begin{pmatrix} y_{1t-2} \\ y_{2t-2} \\ y_{3t-2} \end{pmatrix} + \begin{pmatrix} u_{1t} \\ u_{2t} \\ u_{3t} \end{pmatrix} \qquad (1.2)$$

The coefficient matrix, A_0, reflects the instantaneous relationships between the variables at time t, the coefficient matrix, A_1, reflects the impact of the variables in the immediately preceding time period (t-1) on the current behavior of the system, and similarly, the coefficient matrix, A_2, reflects the impact of the variables from two time periods ago (t-2) on the current system behavior. In other words, the current value of y1t is modeled as a function of the current values of y_{2t} and y_{3t}, the immediately prior values of $y_{1t\text{-}1}$ and $y_{2t\text{-}1}$ and $y_{3t\text{-}1}$, and the even more distal values of $y_{1t\text{-}2}$, $y_{2t\text{-}2}$, and $y_{3t\text{-}2}$ from two time periods prior to the current observations. The general model also frequently includes deterministic terms such as intercepts or trend parameters but they are not represented in (1.1) because the current focus is on the dynamics of the process. Equation 1.1 could be viewed as the dynamic model applied to the residuals of a simple regression on each time series that includes an intercept, trend term(s), and cyclical terms (if relevant). This is a very common model in the multivariate time series literature and Lutkpohl (2005) provides an excellent, detailed description of the model.

Unfortunately, the VAR(p) model in (1.1) is not identified and, just as in the case of structural equation modeling, certain restrictions must be placed on the coefficients to yield an identified model. The most common method of imposing identifying restrictions on the model in (1.1) is to restrict the A_0 matrix to an identity matrix (i.e., $A_0 = I_K$) and the resulting process is referred to as a reduced form VAR(p) process. These restrictions are analogous to restricting the loading of one indicator for each latent variable to 1.0 to provide a scale for the latent variable in structural equation modeling. These restrictions are so common that reduced form VAR(p) models are typically just referred to as the VAR(p) model. One result of these restrictions is that any instantaneous or contemporaneous relationships among the variables is shuttled to the error terms yielding u_t that are contemporaneously correlated and a non-diagonal Σ_u. Another result is that the coefficients in the A_1, …, A_p matrices are a function of both the coefficients at the given lag and the unestimated coefficients in A_0 representing contemporaneous relations among the variables. Separate ordinary least squares estimation of each equation in (1.1) is consistent, asymptotically efficient and equivalent to the maximum likelihood estimator (Hamilton, 1994).

The reduced form model in (1.1) summarizes the instantaneous and intertemporal relations among the variables. However, the dynamic relations among the variables is difficult to discern from the estimated coefficients in the A_i matrices. Also, the contemporaneous influences are represented in the covariance matrix of the residuals. Three general methods are typically used to simultaneously reflect the instantaneous and lagged relations among the time series being analyzed: Impulse response functions,

variance decompositions, and Granger-causality estimates. The focus here will be on impulse response functions.

Impulse response functions represent the marginal responses of the variables in the system to an impulse, perturbation, or change in one of the other variables in the system. The impulse responses are nonlinear functions of the coefficients in (1.1) such that

$$\phi_{ij,h} = \phi_{ij,h}(A_0, A_1, \mathrm{K}\ A_p), \tag{1.3}$$

where the $\phi_{ij,h}$ represent the response of variable *i* to an impulse in variable *j*, *h* periods ago. Viewing the $\phi_{ij,h}$ as the ij^{th} element of the matrix Φ_h, the impulse responses may be computed recursively as

$$\Phi_h = \sum_{j=1}^{h} \Phi_{h-j} A_j, \qquad h = 1, 2, \mathrm{K}\ , \tag{1.4}$$

where $\Phi_0 = I_K$. In general, the $\phi_{ij,h}$ may be viewed as sums of products of the coefficients in the A_i matrices. The impulse responses, along with their associated confidence intervals, are typically depicted graphically across a limited number of time periods to interpret the dynamics of how a change in one variable impacts one of the other variables over time.

Panel Analysis

To this point the description of the VAR(p) model has been based on a data structure where multiple time series are observed on a single unit. Longitudinal data structures in psychology, however, invariably reflect time series assessed on multiple units (e.g., individuals). Numerous generalizations of the VAR(p) model have been developed that incorporate various forms of unobserved unit or cross-section heterogeneity into the estimation procedure (e.g., Anderson & Hsiao, 1981; Arellano & Bond, 1991; Holtz-Eakin, Newey & Rosen, 1988). The Generalized-Method-of Moments (GMM) estimators developed by Arellano and Bond (1991) and Arellano & Bover, (1995) are useful when the time dimension of the panel data is small (e.g., T < 30) but the fixed effects estimator for dynamic panel data (also known as within-groups or least squares dummy variables estimation) is efficient and has negligible bias in large T panels (Gaduh, 2002; Judson & Owen, 1999) and do not suffer from weak instrumentation problems (e.g., Kruiniger, 2000; Hahn et al., 2001). The fixed effects estimator makes it possible to model Cross sectional heterogeneity due to omitted variables differ between cases but are constant over time. This analysis is analogous to allowing individuals to have different intercepts in a longitudinal multilevel model.

Method

Participants. This study collected data from 19 undergraduate students recruited from psychology classes at a large mid-western university. Participants received extra-credit for their initial participation and earned monetary compensation by continuing the study for nine follow-up sessions. The sample was predominantly Caucasian (70%), 60% of participants were female, and the mean age was 20 years old.

Procedure. Upon arrival at the lab, participants received a brief training (approximately 15 minutes) on the task – a complex PC-based simulation of a radar tracking task. After training, participants were given a chance to review the task manual for three minutes, and then perform in a four minute, unscored practice trial. This practice trial only took place during the initial experimental session, and not in the follow-up sessions. Within each session, participants completed nine (9) trials of the task, each lasting four minutes and five seconds. Each trial was preceded by study during which participants were given time (three minutes for the first three trials, one minute thereafter) to study the task manual. Participants had to learn how to hook contacts, query information about these contacts (such as their priority), and then make decisions based on the information. Each trial was followed by feedback and trainees were given fifteen seconds to review their performance on the previous trial. After receiving feedback they set overall score goals for the upcoming trial. This basic design was repeated for nine (9) addition experimental sessions yielding a total of 89 cycles of goal setting, effort investment, and performance feedback.

Task scenarios were designed to prompt learning and resource allocation. The basic task required participants to learn how to hook contacts, query information about these contacts (such as their priority), and then make decisions based on the information. Contacts were distinguished as high and low priority, and participants were instructed to only focus on high priority contacts. In addition, contacts were distinguished as individual and team contact types, along with individual contacts belonging to the virtual teammate. Participants were instructed to only process those contacts that were their responsibility as an individual and a member of the team (i.e. individual and team contacts). The display was also demarked by two perimeters, represented by concentric circles. Participants lost points when contacts penetrated the perimeters, and lost points additional points for every second a contact remained unprocessed inside the perimeter. Effective processing necessitated that participants monitor their entire airspace by zooming the range on the display to monitor activity on both perimeters, query contact priority, and prevent high priority contacts from penetrating the defensive perimeters.

Measures. Goal setting, effort, and performance were the central measures for this investigation. For each trial, effort was computed as a linear composite of a number of behavioral activities undertaken in the task including hooking contacts, making priority or cue queries about contacts, processing contacts, and zooming the range on the radar display. Goals were assessed by asking participants to write down their score goal for the next round after each trial. Specifically, participants were asked: "What is your goal for the overall score for the next round?" Performance was computed by summing participants' scores on low priority contacts, high priority contacts, and perimeter penetrations. Participants gained 200 points for correctly processing high priority contacts and lost 200 points for incorrectly processing high priority contacts. If a high priority contacts crossed one of the two defensive perimeters than participants lost 100 points and were deducted 5 points for each second the high priority contacts was inside the defensive perimeter. Finally, participants lost 400 points for processing low priority contacts. Effort investments result in performance only to the extent that correct decisions are made about how to process contacts.

Results

Figure 3.1 presents the multiple time series of goal, effort, and performance for each of the nineteen participants in the study. There are a number of interesting patterns in the data. First, participants 162, 265, 336, and 385 set goals that are consistently lower than their performance. There is no existing explanation for this pattern in the self-regulation literature. Second, participants 237 and 378 do not appear to be setting goals in a manner that is sensitive to their performance. Their goals are consistently set substantially higher than their highest levels of performance on the task. Third, many of the participants (e.g., 165, 223, 304, 336, 377, 380) show a calibration period where goals are initially set either too low or too high relative to actual performance and then gradually converge to levels that are consistent with the observed performance levels. Fourth, some participants show much greater variance in goal setting over time than do others (e.g., 289, 389). It is unclear whether these participants are overly sensitive to performance feedback or whether some other process accounts for the heterogeneity? Finally, visual inspection of the three time series does not suggest a clear pattern of co-movement.

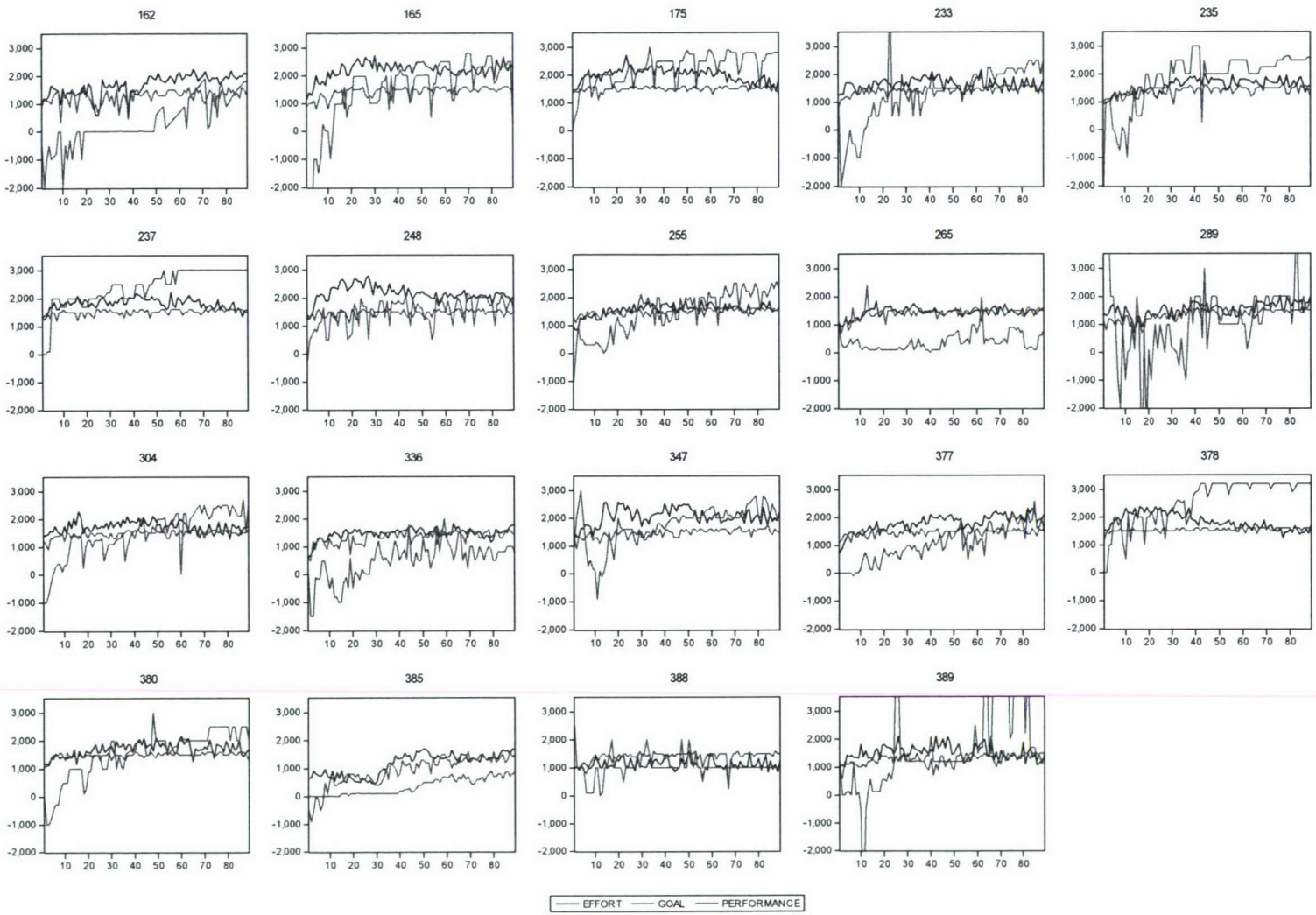

162
165
175
233
235
237
248
255
265
289
304
336
347
377
378
380
385
388
389
EFFORT
GOAL
PERFORMANCE

Figure 3.1

The results of a panel VAR analysis are presented in the following section. First, a panel unit root tests is used to evaluate whether the time series may be modeled as a stationarity process. Second, the process of determining the order of the panel VAR is described. Third, the panel VAR analysis is performed and reported. Finally, panel impulse response functions are computed to interpret the system dynamics.

Stationarity. It is well-known that the common unit root tests, such as the augmented Dickey-Fuller and Phillips-Perron tests, have low power to reject the unit-root null hypothesis. Consequently, many stationary series are analyzed as if they were non-stationary. The use of panel data in the evaluation of stationarity substantially improves the power to reject a false unit-root null hypothesis (Said & Dickey, 1984). The Im, Pesaran, and Shin (1997) panel unit root test was used in this analysis because that data are balanced and this test does not impose the restriction that all panel members share a common autocorrelation coefficient and allows for heterogenerous variances. The Im, Pesaran and Shin (1997) procedure addresses the low power associated with single series unit-root tests by averaging the test statistics across the panel members and assuming i.i.d. errors. Drift and a linear time trends were included in all evaluations using this test. The standardized t-bar statistic (W) from the Im, Pesaran and Shin approach rejected the unit-root null hypothesis for all three series: goal (-6.81, $p < .01$), effort ($W = -9.60$; $p < .01$), and performance ($W = -13.86$; $p < .01$).

Order Selection. The order (i.e., number of lags) of the panel vector autoregressive model used to analyze the data was determined by examining the lag length selected using the Akaike Information Criterion (AIC) for vector autoregressive models computed on each person's data separately. In one case, the AIC identified a lag of three. In all other cases, the selected lag length was either one or two. Based on these results, it was concluded that the panel vector autoregressive model should be performed using an order of two.

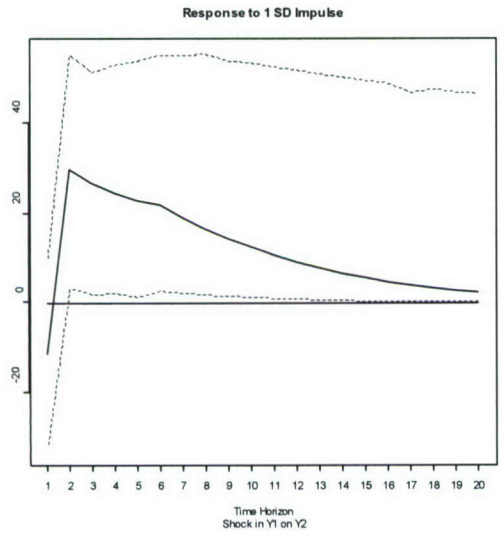
Panel Vector Autoregressive Results. As discussed above, the fixed effects estimator for dynamic panel data (e.g., Baltagi, 2001) was used to model cross sectional heterogeneity due to omitted variables that differ between cases but are constant over time. The model coefficients and equation R^2 fit indices from the fixed effects, panel VAR(2) analysis are presented in Table XX. Coefficients in bold face font are significantly different from zero ($\alpha = .05$) based on robust standard errors. The coefficients in this table result from fitting the reduced form model and so should be interpreted cautiously, if at all.

Table 3.1. Panel VAR(2) coefficients and R^2 indices.

	Lag = 1			Lag = 2			
	Goal	Effort	Perf	Goal	Effort	Perf	R^2
Goal	**0.41**	-0.09	**0.46**	**0.19**	**0.18**	-0.17	0.65
Effort	-0.01	**0.44**	0.03	0.01	**0.27**	0.03	0.58
Perf	-0.01	0.03	**0.26**	0.00	**0.05**	**0.20**	0.40

Impulse Response Analysis. Impulse response functions were computed and graphed to examine the system dynamics estimated in the panel VAR analysis using a cholesky transformation of the residual covariance matrix. Figures 3.2 - 3.4 present the impact of a one standard deviation impulse in goals, effort, and performance respectively on the other two variables in the system. The solid line depicts the estimated impulse response and the dashed lines depict 95% confidence intervals. Closed-form confidence intervals do not yet exist for panel VAR models and so the confidence intervals were computed using the bootstrap method presented by Runkle (1987). With respect to an impulse in goal, both effort and performance show a significant response but performance appears to respond more to a change in goal than effort. This pattern is curious given that effort is thought to be the primary vehicle for translating goals into performance (e.g., Locke and Latham, 1990). Further, for both effort and performance, the impact of the impulse in goal dies off slowly suggesting that goals can have a relatively long lasting impact on both effort and performance. An impulse in effort results in a strong and long-lasting impact on goals. The impact on performance is significant and also dies out slowly but the magnitude of the impact is relatively small in comparison to the other effects depicted in Figures 3.2 - 3.4. Finally, an impulse in performance shows a strong impact on subsequent effort and somewhat lower, but significant, impact on subsequent goals. In all, the system dynamics have the characteristics of a simultaneous feedback system where all variables impact subsequent levels of all other variables.

Goal ⇒ Effort



Goal ⇒ Performance

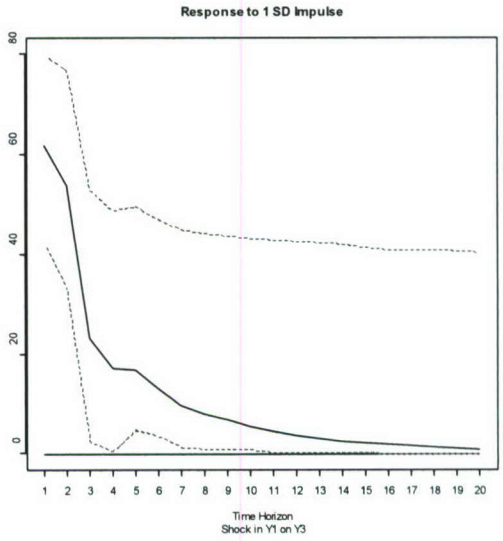
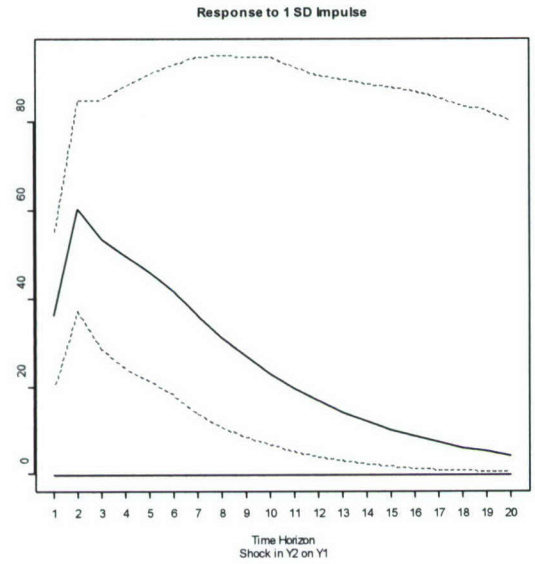


Figure 3.2. Response to a one standard deviation impulse in Goal.

Effort ⇒ Goal



Effort ⇒ Performance

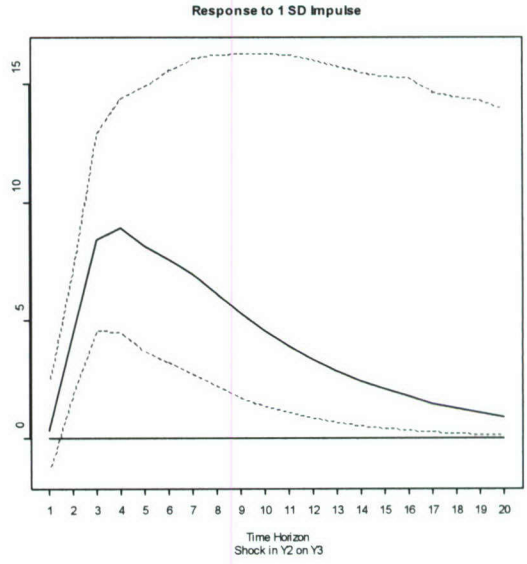
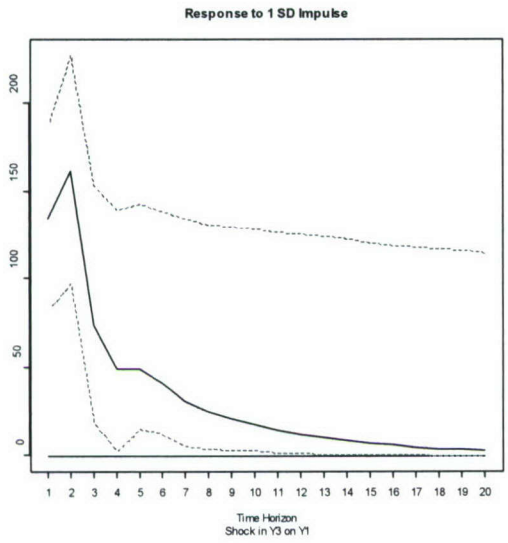


Figure 3.3. Response to a one standard deviation impulse in Effort.

Performance ⇒ Effort



Performance ⇒ Goal

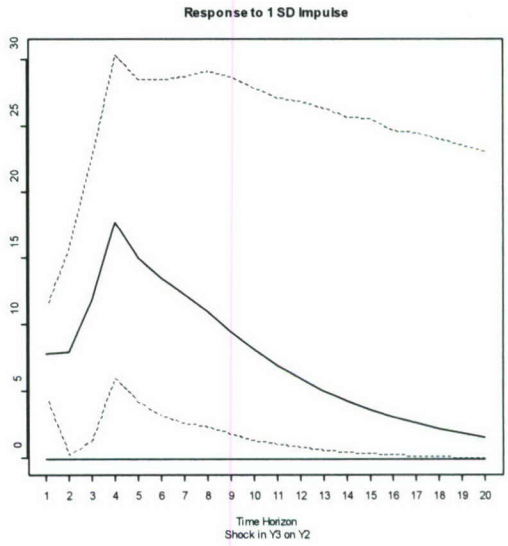


Figure 3.4. Response to a one standard deviation impulse in Performance.

Summary and Conclusions

The results presented above are consistent with the dynamics implied by a classic feedback process. It appears that changes in goals result in immediate and lasting impacts on effort and performance. Similarly, effort impacts goals and performance and performance impacts goals and effort over time. In other words, each of these variables in the self-regulatory system dynamically interact to yield the system's (i.e., individual's) behavior. To the best of our knowledge this is the first attempt to use modern stochastic methods to model the dynamics of human regulation at the level of individual behavior.

Clearly, this initial modeling attempt has numerous and substantial limitations. However, two limitations stand out. First, these results do not demonstrate causality and unmodeled third variables may actually be responsible for the observed patterns of co-movement among the respective time series. However, the patterns are consistent with a very large theoretical literature and provide a first, promising view of the dynamics underlying the regulation of behavior. Second, the current approach allowed for time-invariant, unobserved heterogeneity. However, the underlying dynamics of the process (i.e., slopes) were assumed to be homogeneous across individuals. This assumption is likely unwarranted and further modeling efforts are required to investigate this issue.

Overall Conclusions

The research in this series of projects examining the implications of multiple goal regulation on self-regulation, resource allocation, and adaptation has once again provided several promising findings that can inform the development of practical applications designed to improve performance on complex tasks (i.e., simulation design, training support, decision aids) and, perhaps more importantly, extensions to the dynamic goal regulation research paradigm we have evolved and theoretical developments that make better use of our ability to model the dynamics of multiple goal resource allocation processes with greater precision.

With respect to practical applications, the findings from experiments 1 and 2 confirm that rapidly cycling feedback on the state of the environment relative goal-performance discrepancies was instrumental to participant situation assessment, strategy selection, and performance adaptation following changes in the environment when compared to conventional KOR (or end of trial feedback) or dynamic real-time feedback that updated more slowly. Although there was some potential concern that rapidly cycling feedback could be too salient, thereby drawing on needed regulatory resources, there was no evidence for detriments. Thus, one would conclude that feedback needed to support resource allocation needs to be provided at a rate that is commensurate with the cycle time necessary for goal-performance discrepancy updates to synchronize with rates of change in the performance environment. This principle can be used to guide simulation design, training support, and embedded decision aids.

In addition to replicating the primary findings of experiment 1, experiment 2 also highlighted the effectiveness of inducing metacognitive processes as a means to enhance trainee self-regulation, resource allocation, and adaptation. Self-regulation as a psychological process is often beneath the level of conscious awareness. Metacognition is the conscious awareness and active management of one's cognition, behavior, and affect as one strives for goal accomplishment and, therefore, a means to make self-regulatory processes salient. We hypothesized that inducing active monitoring of one's goals, current states (i.e., feedback indicated goal-performance discrepancies), and future states (i.e., adjustments of effort and strategies) would enhance resource allocation and adaptation and, moreover, that metacognitive induction would supplement the prior findings for feedback cycle time. Those hypotheses were largely supported. The metacognitive induction provided a distinct benefit to self-regulation, resource allocation, and adaptation. It can be applied on its own or combined effectively with feedback cycle time updates to enhance resource allocation. One practical advantage of metacognition induction is that it can be induced in a variety of different ways including the question probes used in this research embedded in technology; directions, instructions, or training; or even by verbal questions posed by an instructor. Thus, it is a design principle with broad application potential.

With respect to the evolution of our resource allocation research paradigm and theoretical extension...

Experiment 3 represents an initial investigation of the dynamic processes underlying effort allocation and performance in a simulated task environment. This research is still in its infancy and so practical applications remain unclear at this time. However, with further work along these lines we hope to be able to identify important levers that can be used to push self-regulatory dynamics in directions that yield high levels of performance that are maintained over time. The current research adds to our knowledge of how setting goals or objectives and providing clear and immediate performance feedback may be used push performance to new plateaus and maintain the performance gains. Future work in this area is needed to investigate the dynamic process underlying other key levers including affective reactions, such as frustration and dissatisfaction, and performance expectancies.

We see this research heading in two complimentary directions. First, as just highlighted, more comprehensive models of human performance dynamics need to be developed and empirically evaluated. We have developed a promising research methodology for investigating this issue and look forward to identifying the reciprocally causal mechanisms responsible for performance on complex tasks in both individual and team performance contexts. Given the multivariate time-series data needed to explore these issues, this research is resource intensive.

The second research direction focuses on the exploration of the mechanisms that support and are responsible for multiple goal regulation, resource allocation, and adaptation. Our intended approach to this issue is to use agent-based methods (e.g., reinforcement learning) to identify how optimal resource allocation policies may be learned in complex multi-goal environments such as those that exist in our primary research

simulation task. Then, we intend to compare actual human learning and performance on the identical task to identify aspects of human behavior and learning that are responsible for sub-optimal decisions and performance. Human learning and performance may be improved by incorporating the reinforcement learning mechanisms that frequently result in optimal performance into human training and decision support processes. In a complementary fashion, we believe that reinforcememt learning approaches may be improved by incorporating the known strengths that humans possess for rapid information integration, pattern recognition, resource allocation, and real-time decision making. Together, such a dual pronged approach would enable the development of much more robust and adaptive training and decision support systems for complex command and control tasks commonly used by the US Air Force.

Research Program Summary: Secondary Studies

Enhancing the Effectiveness of Work Groups and Teams

Steve W. J. Kozlowski and Daniel R. Ilgen

A monograph of this research project was recently published:

Kozlowski, S. W. J., & Ilgen, D. R. (2006). Enhancing the effectiveness of work groups and teams. *Psychological Science in the Public Interest*, 7, 77-124.

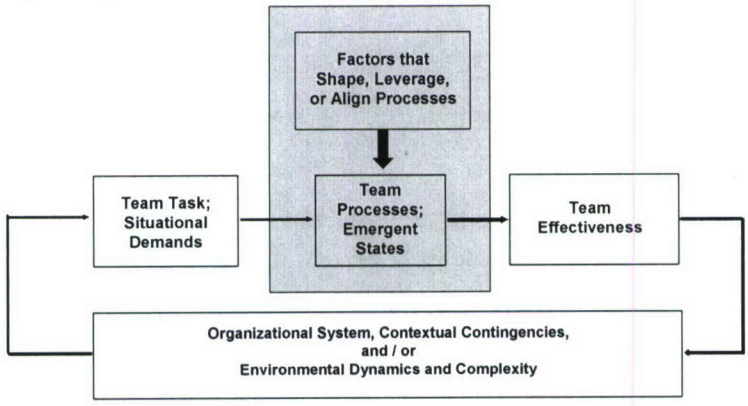
A synopsis of the project was also recently published:

Kozlowski, S. W. J., & Ilgen, D. R. (2007, June/July). The science of team success. *Scientific American Mind*, 54-61.

Teams of people working together for a common purpose have been a centerpiece of human social organization ever since our ancient ancestors first banded together to hunt game, raise families, and defend their communities. Human history is largely a story of people working together in groups to explore, achieve, and conquer. Yet, the modern concept of work in large organizations that developed in the late 19th and early 20th centuries is largely a tale of work as a collection of individual jobs. A variety of global forces unfolding over the last two decades, however, have pushed organizations world-wide to restructure work around teams to enable more rapid, flexible, and adaptive responses to the unexpected. This shift in the structure of work has made team effectiveness a salient organizational concern.

Teams touch our lives everyday and their effectiveness is important to well being across a wide range of societal functions. There is over 50 years of psychological research – literally thousands of studies – focused on understanding and influencing the processes that underlie team effectiveness. In this monograph, we sift through this voluminous literature to identify *what we know, what we think we know, and what we need* to know to improve the effectiveness of work groups and teams. We begin by defining team effectiveness and establishing critical conceptual considerations that underlie our approach to understanding it. We then turn to our review which concentrates primary attention on topics that have established well-developed theoretical and empirical foundations to ensure that conclusions and recommendations are on firm footing. As illustrated below, we first focus attention on cognitive, motivational-affective, and behavioral *team processes* that enable team members to combine their resources to resolve team task demands and, in so doing, achieve effectiveness. Then, having established critical team processes that enable team effectiveness, we identify *interventions or levers* that can shape or align team processes and, in that sense, provide tools and applications for improving team effectiveness. Topic specific conclusions and recommendations are drawn throughout the review.

Figure 1. *Conceptual Framework and Review Focus.*



- Environmental dynamics and complexity drive team task demands
- Team processes align team member resources to fit demands
- Team outputs influence the environment
- Cycles are reciprocal over time

Team cognitive processes examined include *team climate, team mental models and transactive memory*, and *team learning*. Team and unit climate represent shared understanding of the key goals or 'strategic imperatives' driving the team task environment. It creates the motivational press that directs team member resources and has been linked to team effectiveness. Team mental models represent cognitive structures that organize important team knowledge areas, whereas transactive memory represents team members' knowledge about 'who knows what' that enables unique individual knowledge to be accessed by all team members. Together, the two concepts provide a means to capture collective team knowledge relevant to performance. Finally, team learning is more of a representation of the process by which collective knowledge and skills are acquired. Looking across these team cognitive processes, team climate is mature and application ready, whereas team mental model research is less well developed although the concept is application ready. Transactive memory shows preliminary application potential and team learning is still undergoing basic conceptual development.

Team interpersonal, motivational, and affective processes considered include *cohesion, efficacy, and potency; affect, mood, and emotion;* and *conflict*. Among these concepts, cohesion, efficacy, and potency have well developed research foundations linking the processes to team effectiveness. Team cohesion entails team member attraction, task commitment, and loyalty. Team efficacy represents a shared confidence in the team's ability to accomplish its task, whereas team potency is a more generalized shared perception of team competence. All three team processes evidence the potential to be influenced, and therefore are application targets. Research on the other topics is less well developed, so that although they are likely to be important contributors to team effectiveness, the conceptual and research foundations need more elaboration before solid recommendations can be made.

The team behavioral processes that we examined focus on team *coordination, cooperation, communication; enabling team member competencies; and the cognitive-affective-behavioral processes by which teams dynamically regulate and adapt their performance*. These topics are a challenge to summarize succinctly. Suffice it to say that there is a well developed foundation for the person competencies that enable action and that underlie team coordination and performance, and there is a confluence of promising work that is elaborating the performance regulation and adaptive processes underlying team effectiveness. Several techniques and approaches within this area can be applied to enhance team effectiveness in specific situations.

Turning to the interventions or levers of the team processes highlighted above, our review centered on *team design, team training and development, and team leadership*. There is a substantial research foundation supporting specific interventions that cut across these areas, although team development is the one area where we have lots of theory and little solid data. Nonetheless, there is considerable actionable knowledge to improve the design of teams and their context, and to use team training to provide process underpinnings and leadership to shape process development. Our recommendations are to apply the science to enhance team processes and team effectiveness.

In sum, there is a solid foundation for concluding that there is an emerging science of team effectiveness and several means to improve it. In the concluding section, we summarize our primary findings to highlight specific research, application, and policy recommendations for enhancing the effectiveness of work groups and teams.

A Motivated Action Theory Account of Goal Orientation

Richard P. DeShon and Jennifer Z. Gillespie

A journal article reporting this research project was published:

DeShon, R. P. & Gillespie, J. Z. (2005). A motivated action theory account of goal oriented behavior. *Journal of Applied Psychology, 90*, 1096 - 1127.

Working in a team imposes individuals with multiple roles and duties that are continuously updated as the environment changes over time. In order to successfully adapt to the rapidly changing environment, team members often find themselves making dynamic decisions on where and how to allocate their cognitive and behavioral resources across competing demands. These dynamic resource allocations involve a continuous process of dynamic monitoring of multiple goal states and discrepancies with respect to current performance, and making good decisions. Deciding how to best allocate limited resources across multiple goals is fundamental for the effective coordination of team members' behaviors, which enable the team to perform at its optimal level.

One of the essential motivational variables that predict resource allocation decisions of individuals is achievement motivation. Achievement motivation predicts how individuals allocate their resources toward different requirements in achievement settings, which in turn, leads to learning- and performance-related behaviors that are critical for adaptation in changing environments. Previous research on achievement motivation, however, does not have an adequate conceptual framework for resource allocation decisions that occur across multiple goals and over time. Working in teams requires individuals to dynamically shift their goals over time to meet the requirements of their environments. Knowing how different goals are related and how shifting between multiple goals occurs over time are critical for advancement of team resource allocation research. Yet, achievement motivation research has an inconsistent perspective on how stable the goals are, how many goals individuals pursue, and how multiple goals are determined by the achievement motivation of individuals. Based on the extensive literature review in the paper, we point out the conceptual and methodological inconsistency in the current achievement motivation literature that interfere with the development of integrated multiple goal framework that is essential for examining dynamic adaptive behaviors of individuals in teams.

As illustrated in the following Figure 5.1, we developed Motivated Action Theory (MAT) which encompasses numerous achievement motivation perspectives and advances previous achievement motivation studies by imposing an integrated theoretical framework for a resource allocation mechanism among multiple goals. Using the MAT framework, we argued that achievement motivation consisted of hierarchical structures of multiple goals in which high-level goals distal and desired status and lower level goals are the means to achieve the higher level goals. Goals at different and adjunct levels are massively interconnected which enable individuals to rapidly shift their goals at cross- and within-levels. MAT puts achievement motivation in a dynamic profile perspective in which multiple arrays of goals can dictate individuals' behaviors over time. Therefore, over a period of time, a person may switch between the various achievement goals and perform sequential actions designed to reduce discrepancies on more than one higher level goal. Thus, a person can flip back and forth between a performance and learning achievement goal many times over the course of working on a task. Accordingly, individuals pursue multiple goals over time through the dynamics of interaction between their predisposition in achievement motivation and the activation of goals that are imposed by changes in their environment.

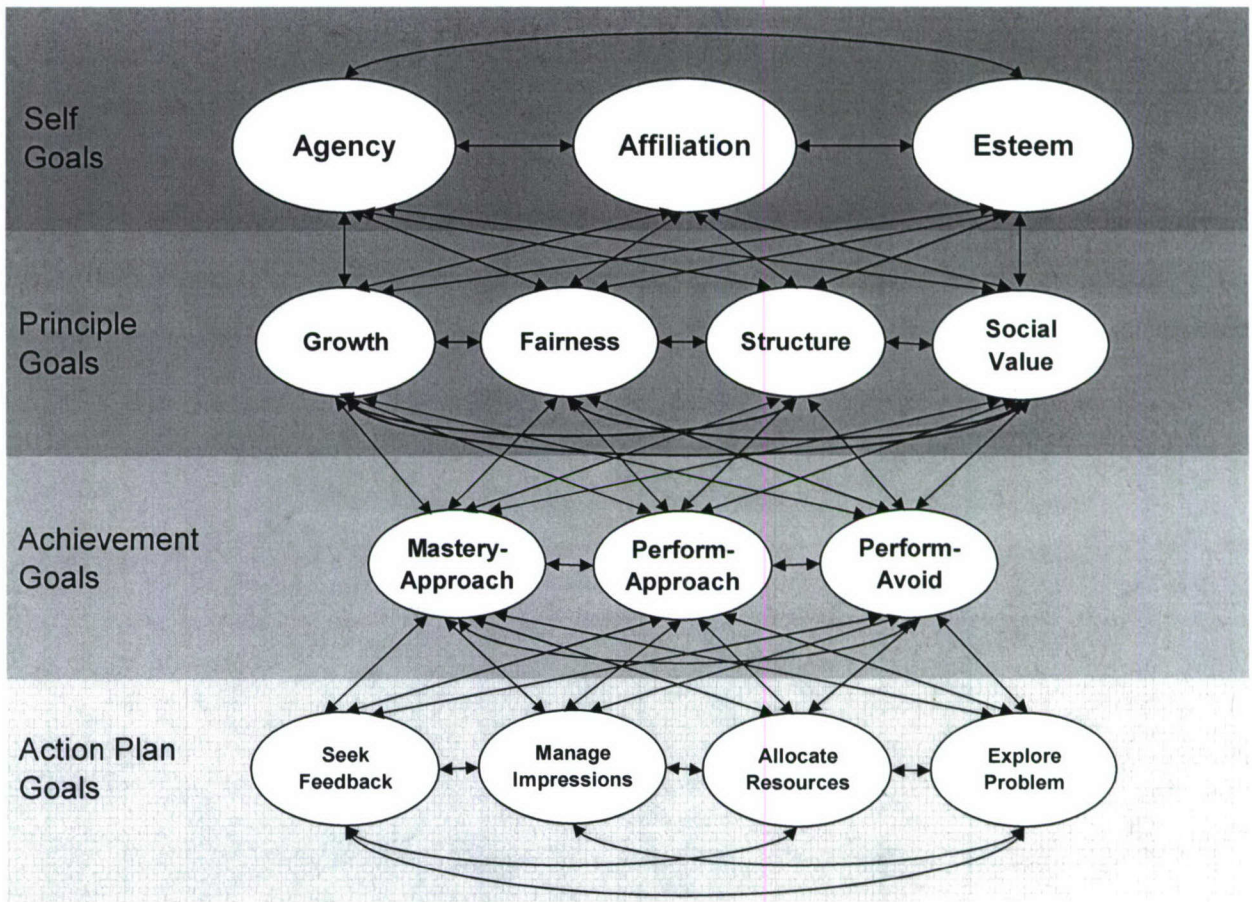


Figure 5.1. Motivated Action Theory Model of the Goal Orientation Hierarchy

Locomotion-Assessment, Action-State Orientation, and Goal Orientation: A Case for Higher Order Motives

Anthony S. Boyce, Goran Kuljanin, Guihyun Park, Paul G. Curran,
Steve W. J. Kozlowski and Richard P. DeShon

Manuscript Under Review

Self-regulatory process models are the dominant approach to the study of motivation and the impact of motivation on human cognition and behavior. Although numerous models exist (e.g., Bandura, 1991; Carver & Scheier, 1990; Frese & Zapf, 1994; Hacker, 1985; Kuhl, 1985; Locke & Latham, 1991), they share a core set of features including goal choice, planning and effort allocation to achieve the chosen goal, feedback monitoring to evaluate progress toward the goal, and affective and cognitive reactions to goal progress information. Further, virtually all self-regulatory models assume that behavior is goal directed and that goals are hierarchically structured such that goals at high levels of the hierarchy specify why actions are undertaken and lower level goals specify how the higher-level goals can be met (e.g., Carver & Scheier, 1998; DeShon & Gillespie, 2005, Powers, 1973).

The development of self-regulatory models initiated the pursuit of individual differences in the self-regulatory process. Individual differences in the self-regulatory process address the types of goals that individuals choose to pursue (e.g., mastery goals vs. achievement goals or approach vs. avoid goals) and the manner in which the goals are pursued (e.g., planning vs. doing, locomotion vs. assessment, state vs. action). If goals are hierarchically structured, then the reason why individuals adopt different regulatory goals or methods for achieving the goals may be due to differences between individuals on higher level goals (DeShon & Gillespie, 2005).

This research analyzed two datasets that demonstrated the existence of two higher-order motives of task- and ego-involvement and their predictive relationship with self-regulatory processes such as goal commitment, self-efficacy, and cognitive effort. After explaining theoretical and operational similarities between trait goal orientation, assessment-locomotion, and action-state orientation, Study 1 concluded that a second-order confirmatory factor analysis fit the data as well as a first-order confirmatory factor analysis. As shown in Figure 6.1 below, mastery goal orientation, locomotion, and hesitation (a subscale of action-state orientation) loaded highly on task-involvement, whereas performance goal orientation, performance-avoid goal orientation, assessment, and preoccupation (a subscale of action-state orientation) loaded highly on ego-involvement.

- First order model
  - **Sample A: X^2=2936(1203), RMSEA=.04, SRMR=.05**
  - *Sample B: X^2=4648(1059), RMSEA=.04, SRMR=.05*
- Second order model
  - **Sample A: X^2=3336(1216), RMSEA=.04, SRMR=.08**
  - *Sample B: X^2=5309(1072), RMSEA=.05, SRMR=.07*

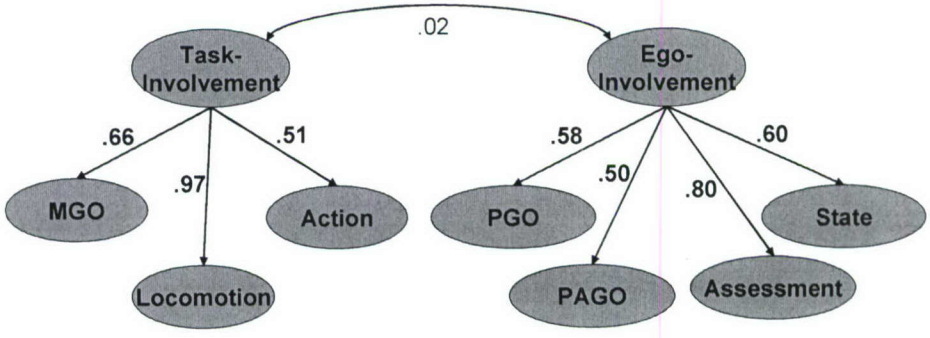


Figure 6.1. Study 1 Results.

Moreover, as shown in Figure 6.2 below, Study 2 demonstrated that task-involvement affected goal commitment, self-efficacy, and cognitive effort positively whereas task-involvement negatively affected off-task thoughts. On the other hand, ego-involvement positively affected cognitive effort whereas ego-involvement negatively affected self-efficacy and affect.

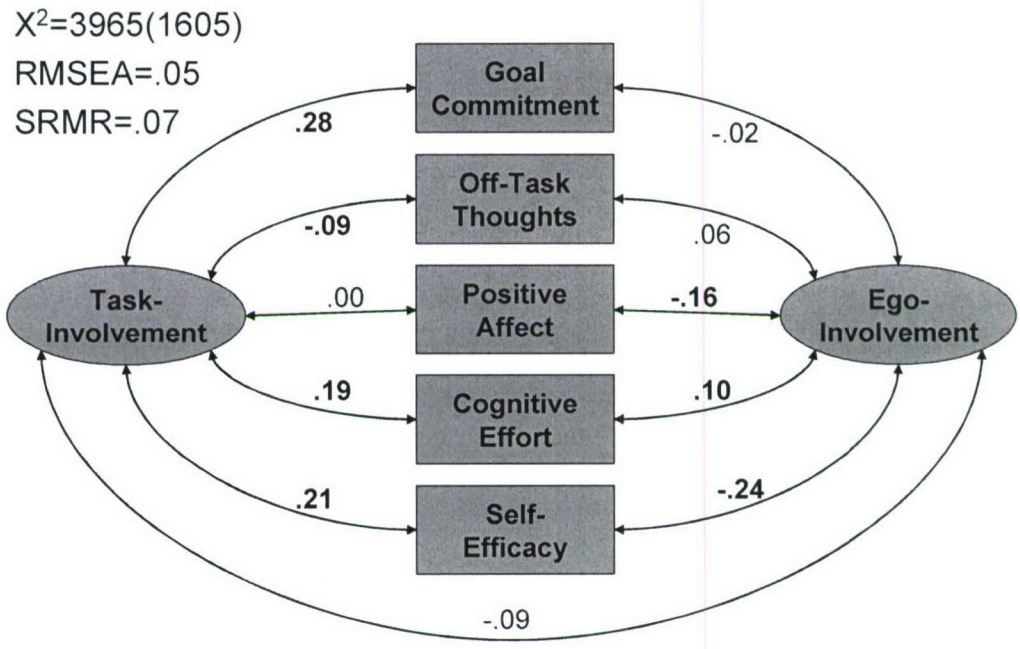


Figure 6.2. Study 2 Results.

The current study aimed to advance the self-regulation literature by demonstrating that two higher order motives of task- versus ego-involvement encompass these three sets of individual difference constructs. From a conceptual perspective, this hierarchical organization is consistent with motivated action theory (DeShon & Gillespie, 2005) which proposes that individual variability in the selection of goals and the means by which they are pursued is due to differences on higher level goals. It is also consistent with other empirical findings that support the presence of higher order factors accounting for other lower level self-regulatory constructs (e.g., Elliot & Church, 1997; Elliot & McGregor, 1999; Heubeck et al., 1998). Our results suggest that even though previous research has proposed that these sets of individual difference constructs have unique theoretical origins, they do, in fact, share many properties regarding individual differences in self-regulatory processes that are captured as parsimonious higher order task- versus ego-involvement motives. Therefore, our findings suggest that a gap exists in the self-regulation literature regarding the conceptualization of unique individual difference constructs and their empirical distinctiveness.

With respect to parsimony, one could argue that a conceptualization of higher order task- versus ego-involvement motives is the foundation position against which claims for the distinctiveness of unique constructs have to be assessed. However, we feel it is somewhat premature to conclude that these individual differences do not have unique contributions in predicting individual differences in self-regulation. It is not clear whether the observed overlap among the individual difference measures studied in this research is due to the existence of two overarching motives that are the common foundation for the individual difference constructs or to inadequate operationalization of key theoretical nuances in the construct measures, or both. Future theory development and empirical research needs to more clearly delineate the constructs to capture their nuances and unique characteristics – if such differences can be made tangible.

It is possible that some of the nuanced distinctions among the construct sets could be important and useful. For example, goal orientation focuses on goal and evaluative reactions to goal progress. Action-state orientation and locomotion-assessment are more focused on the implementation of goal pursuit and its maintenance, but also include evaluative reaction to goal progress. For conceptual progress, we think a more concerted effort is needed to capture individual differences across a full range of self-regulatory phases that

would either solidify a higher order conclusion or might yield more empirically distinctive self-regulatory individual differences. Specifically, self-regulation can be parsed into a more complete series of phases encompassing goal choice, action initiation, action persistence, feedback seeking, and progress reactions. Next, potential individual differences in actions and reactions within each phase can be conceptualized. This would require conceptual and operational revisions to the current constructs and/or the construction of new ones. If higher order motives also capture variance across this more conceptually coherent set of individual difference constructs, there would be firmer support for the hierarchical model. On the other hand, if the phases of self-regulation help to yield empirically distinct individual differences, then we would have some evidence that the higher order factors may be due to a failure to carefully parse distinct phases of self-regulation and to carelessly mix them together. Either outcome would constitute a conceptual and empirical advance in this important area of theory and research.

References

Ahn, S., & Schmidt, P. (1995). Efficient estimation of models for dynamic panel data. Journal of Econometrics, 68, 3-38.

Anderson, T. W., & Hsiao, C., (1981). Estimation of dynamic models with error components. Journal of the American Statistical Association, 76, 589-606.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. Review of Economic Studies, 58, 277-297.

Arellano, M., & Bover, O. (1995). Another Look at the Instrumental Variable Estimation of Error-Components Models. Journal of Econometrics, 68, 29-51.

Baltagi, B. H. (2001). Econometric analysis of panel data. John Wiley and sons.

Bandura, A. (1991). Social cognitive theory of self-regulation. Organizational Behavior and Human Decision Processes, 50, 248-287.

Bell, B. S., & Kozlowski, S. W. J. (in press). Active learning: Effects of core training design elements on self-regulatory processes, learning, and adaptability. Journal of Applied Psychology.

Bell, B. S., & Kozlowski, S. W. J. (in press). Toward a theory of learner centered training design: An integrative framework of active learning. In S. W. J. Kozlowski & E. Salas (Eds)., Learning, training, and development in organizations. Mahwah, NJ: LEA.

Brown, A. L., Bransford, J. D., Ferrara, R. A., & Campione, J. C. (1983). Learning, remembering, and understanding. In J. H. Flavell & E. M. Markman (Eds.), Handbook of child psychology (4th ed., Vol. 3, pp. 77-166). New York: Wiley.

Carver, C. S., & Scheier, M. F. (1990). Origins and functions of positive and negative affect: A control-process view. Psychological Review, 97, 19-35.

Carver, C. S., & Scheier, M. F. (1998). On the self-regulation of behavior. New York: Cambridge University Press.

Chhokar, J., & Wallin, J. A. (1984). A field study of the effect of feedback frequency on performance. Journal of Applied Psychology, 69, 524-530.

DeShon, R. P. & Gillespie, J. Z. (2005). A motivated action theory account of goal oriented behavior. Journal of Applied Psychology, 90, 1096 - 1127.

DeShon, R. P., Kozlowski, S. W. J., Schmidt, A. M., Milner, K. R., & Wiechmann, D. (2004). A multiple-goal, multilevel model of feedback effects on the regulation of individual and team performance. Journal of Applied Psychology, 89, 1035-1056.

Elliot, E. S., & Church, M. A. (1997). A hierarchal model of approach and avoidance achievement motivation. Journal of Personality and Social Psychology, 72, 218-232.

Elliot, A. J., & McGregor, H. A. (1999). Test anxiety and the hierarchical model of approach and avoidance achievement motivation. Journal of Personality and Social Psychology, 76, 628-644.

Frese, M., & Zapf, D. (1994). Action as the core of work psychology: A German approach. In H. C. Triandis, M. D. Dunnette & L. Hough (Eds.), Handbook of industrial and organizational psychology (Vol. 4, pp. 271-340). Palo Alto, CA: Consulting Psychologists Press.

Gaduh, A. (2002). Properties of fixed effects dynamic panel data estimators for a typical growth dataset. CSIS Working Paper Series, WPE 062.

Hacker, W. (1985) Activity: A fruitful concept in industrial psychology. In: M. Frese & J. Sabini, (Eds.), Goal directed behavior: The concept of action in psychology. Hillsdale, NJ: Erlbaum.

Hahn, J., Hausman, J., & Kuersteiner, G. (2001). Bias corrected instrumental variables estimation for dynamic panel models with fixed effects. MIT Working Paper.

Hamilton, J. D. (1995). Time series analysis. Princeton University Press.

Holtz-Eakin, D., Newey, W., & Rosen, S. (1988). Estimating Vector Auto regressions with Panel Data. Econometrica, 56, 1371-1395.

Horvath, M., Scheu, C., & DeShon, R. P. (2001). Longitudinal relationships among goal orientation, goal-setting, and self-efficacy. Presented at the 16th Annual Convention of the Society for Industrial and Organizational Psychology. San Diego, CA.

Heubeck, B. G., Wilkinson, R. B., & Cologon, J. (1998). A second look at Carver and White's (1994) BIS/BAS scales. Personality and Individual Differences, 25, 785-800.

Judson, R. A., & Owen, A. L. (1999). Estimating Dynamic Panel Data Models: A practical guide for Macroeconomists. Economics Letters, 65, 9-15.

Kanfer, R., & Ackerman, P. L. (1989). Motivation and cognitive abilities: An integrative/aptitude-treatment interaction approach to skill acquisition. Journal of Applied Psychology - Monograph, 74, 657-690.

Karoly, P. (1993). Mechanisms of self-regulation: A systems view. Annual Review of Psychology, 44, 23-52.

Klein, H. J., Wesson, M. J., Hollenbeck, J. R., Wright, P. M., & DeShon, R. P. (2001). The assessment of goal commitment: A measurement model meta-analysis. Organizational Behavior and Human Decision Processes, 85, 32–55.

Kluger, A. N., & DeNisi, A. (1996). The effects of feedback interventions on performance: A historical review, a meta-analysis, and a preliminary feedback intervention theory. Psychological Bulletin, 119, 254-284

Kozlowski, S. W. J., & Bell, B. S. (2003). Work groups and teams in organizations. In W. C. Borman, D. R. Ilgen, & R. J. Klimoski (Eds.), Handbook of psychology: Industrial and organizational psychology (Vol. 12, pp. 333-375). London: Wiley.

Kozlowski, S. W. J., & DeShon, R. P. (2004). A psychological fidelity approach to simulation-based training: Theory, research, and principles. In E. Salas, L. R. Elliott, S. G. Schiflett, & M. D. Coovert (Eds.), Scaled worlds: Development, validation, and applications. Burlington, VT: Ashgate Publishing.

Kozlowski, S. W. J., & Klein, K. J. (2000). A multilevel approach to theory and research in organizations: Contextual, temporal, and emergent processes. In K. J. Klein & S. W. J. Kozlowski (Eds.), Multilevel theory, research, and methods in organizations: Foundations, extensions, and new directions (pp. 3-90). San Francisco: Jossey-Bass.

Kozlowski, S. W .J., Toney, R. J., Mullins, M. E., Weissbein, D. A., Brown, K. G., & Bell, B. S. (2001). Developing adaptability: A theory for the design of integrated-embedded training systems. In E. Salas (Ed.), Advances in human performance and cognitive engineering research (Vol. 1, pp. 59-123). Amsterdam: JAI/Elsevier Science.

Kruiniger, H., 2000. GMM estimation of dynamic panel data models with persistent data. Mimeo, Queen Mary, University of London.

Kruglaski, A. W., Thompson, E. P., Higgins, E. T., Atach, M. N., Pierro, A., & Shah, J. Y. (2000). To "do the right thing" or to "just do it": Locomotion and assessment as a distinct self-regulatory imperatives. Journal of Personality and Social Psychology, 79, 793-815.

Kruiniger, H., 2000. GMM estimation of dynamic panel data models with persistent data. Mimeo, Queen Mary, University of London.

Kuhl, J. (1985). Volitional mediators of cognition-behavior consistency: Self-regulatory processes and action versus state orientation. In J. Kuhl & J. Beckmann (Eds.), Action control: From cognition to behavior (pp. 101-128). Heidelberg: Springer.

Kuhl, J., & Beckmann, J. (1994). Volition and personality: Action versus state orientation. Seattle, WA: Hogrefe & Huber.

Locke, E. A., & Latham, G. P. (1990). A theory of goal setting and task performance. Englewood Cliffs, NJ: Prentice Hall.

Locke, E. A., & Latham, G. P. (1991). Self-regulation through goal setting. Organizational Behavior and Human Decision Processes, 50, 212-247.

Lütkepohl, H. (2005). New introduction to multiple time series analysis. Springer.

Meloth, M. S. (1990). Changes in poor readers' knowledge of cognition and the association of knowledge of cognition with regulation of cognition and reading comprehension. Journal of Educational Psychology, 82, 792-798.

Pintrich, P. R. (2003). A motivational science perspective on the role of student motivation in learning and teaching contexts. Journal of Educational Psychology, 95, 667-686.

Pintrich, P. R., Smith, D. A. R., Garcia, T., & McKeachie, W. (1991). A manual for the use of the motivated strategies for learning questionnaire (MSLQ). Ann Arbor: University of Michigan, National Center for Research to Improve Postsecondary Teaching and Learning.

Powers, W. T. (1973). Behavior: The control of perception. Chicago: Aldine.

Ross, G. T. & Soland, R. M. (1975). A branch and bound algorithm for the generalized assignment problem. Mathematical Programming, 8, 91-103.

Runkel, D. E. (1987). Vector Auto regressions and Reality. Journal of Business and Economic Statistics, 5, 437-442.

Said, S. E., & Dickey, D. A. (1984). Testing for unit roots in autoregressive moving average models of unknown order. Biometrika, 71, 599-607.

Salas, E., Dickinson, T. L., Converse, S. A., & Tannenbaum, S. I. (1992). Toward an understanding of team performance and training. In R. W. Swezey & E. Salas (Eds.), Teams: Their training and performance (pp. 3-29). Stamford, CT: Ablex Publishing Corp.

Shiflett, S. (1979). Toward a general model of small group productivity. Psychological Bulletin, 86, 67-79.

Smith, E. M., Ford, J. K., & Kozlowski, S. W. J. (1997). Building adaptive expertise: Implications for training design. In M. A. Qui• ones & A. Dudda (Eds.), Training for a rapidly changing workplace: Applications of psychological research (pp.89-118). Washington, DC: APA Books.

Schmidt, A., & Ford, J. K. (2003). Learning within a learner control training environment: The interactive effects of goal orientation and metacognitive instruction on learning outcomes. Personnel Psychology, 56, 405-429.

Steiner, I. D. (1972). Group process and productivity (pp. 14-66). New York: Academic Press.

Spielberger, C. D. (1983). Manual for the State-Trait Anxiety Inventory (STAI). PaloAlto, CA: Consulting Psychologists Press.

Tushman, M., & Romanelli, E. (1985). Organizational evolution: A metamorphosis model of convergence and reorientation. In L. Cummings & B. Staw (Eds.), Research in organizational behavior (Vol. 7, pp. 171-222). Greenwich, CT: JAI.

Vallacher, R. R., & Wegner, D. M. (1987). What do people think they're doing? Action identification and human behavior. Psychological Review, 94, 3-15.

VandeWalle, D. (1997). Development and validation of a work domain goal orientation instrument. Educational and Psychological Measurement, 8, 995-1015.

Volet, S. E. (1991). Modeling and coaching of relevant metacognitive strategies for enhancing university students' learning. Learning and Instruction, 1, 319-336.

Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS Scales. Journal of Personality and Social Psychology, 54, 1063-1070.