THE SETTING OF PERSONAL GOALS AS A BAYESIAN CALIBRATION PROCESS

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A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

DOCTOR OF PHILOSOPHY

Psychology

2012

ABSTRACT

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While the positive impact of goals on task performance is well documented (Locke & Latham, 1990), there still is little understanding of the way in which people set and revise personal goals over time. Research has found that people change their personal goals over time, often to reduce performance-goal discrepancies (Campion & Lord, 1983; Donovan & Williams, 2003; Vancouver et al, 2001) although how such goal revision proceeds over time has not been clearly conceptualized. This dissertation proposes that personal goal revision proceeds through the process of goal calibration by the mechanism of Bayesian updating. People use performance and performance variance information to better estimate future performance and revise their current personal goals to reflect such information. Bayesian updating has been shown to be a process that influences how people make estimations of a number of factors (Griffiths & Tenenbaum, 2006) and thus should have a similar impact on personal goals. This was tested with 155 college students performing a temporary worker hiring task and setting task related personal goals. Support was found for a goal calibration model better fitting actual participant personal goals compared to a Goal Setting Model, although unexpectedly a constant growth model offered the best fit. The reasons for these results and implications for future work on personal goal setting is discussed.

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Introduction

Dissertation Purpose and Organization

One of the most significant areas of interest to employers is how workers can be motivated to be more productive. Employees working at higher levels of performance have significant impact on the success of companies and their profit margins. This need to motivate workers to perform better and to understand motivational processes has helped drive a great amount of scientific work in both the psychology and management research disciplines. One of the main thrusts of research examining motivational issues has been the impact of goals on increasing performance.

Research examining the effects of goals began around the simple idea of determining whether or not goals have an effect on task performance (Latham & Locke, 2007; Locke, 1968). The answer to that question was found to generally be “yes,” (Locke, 1968; Locke & Latham, 1990), with individuals given goals performing at a higher level than those who were not given goals. Goal setting research was done in an inductive fashion, with little overarching theory, just empirical studies continually examining the effects of goals in varying conditions, environments, and goal levels.

This goal setting work would be given a general theory in Locke and Latham’s 1990 book “A Theory of Goal Setting & Task Performance” that cited a number of meta-analytic results (Chidester & Grigsby, 1984; Mento, Steel, & Karren, 1987; Tubbs, 1986; Wood, Mento, & Locke, 1987) showing that the best types of goals for increasing task performance were specific, difficult and focused on attaining a performance level. Locke and Latham (1990) argued that goal difficulty had a more or less perfectly positive relationship with performance, with harder goals leading to higher levels of performance. Difficult and specific assigned goals offered a push for individuals to invest more effort and work harder than they would have without an externally imposed goal. These findings have been implemented in actual organizational practice through systems such as Management by Objectives (Drucker, 1976; Rodgers & Hunter, 1991) and the ProMES system (Pritchard 1990).

While the results summarized in Locke and Latham (1990) might be viewed as an answer to the question of how to best motivate individuals through goals, and how the goal motivational process works, the studies used lack some significant aspects of real world goal setting. Most goal setting work has focused on single, static goal situations and between subject effects (Locke & Latham, 1990; Vancouver, Thompson, & Williams, 2001). Groups given different goals at an initial time point are compared against each other either for performance level, learning level, or a desired other outcome at a later time point. If one group has a statistically significant higher level of the outcome at the later time point, the goal is considered to be better. The goals given in such designs are static and unchanging. Such work reveals how different goals can change individual performance at the between subject level, but offers little information on the important issue of how an individual reacts to a given assigned goal and uses that goal over time. This within person goal process has been under researched and, thus, is poorly understood.

Based on the empirical research base that has looked at within person assigned goal effects over repeated trials, there is good reason to believe that the effect of assigned goals is not robust over time. This dissertation proposes a major reason for the lack of robustness is that the personal goals adopted by people become more and more disconnected from assigned goals over time through a process called goal calibration. In goal calibration individuals use performance information gained from repeated trials of a task to inform personal goal revision. Goal calibration argues that previous performance becomes more important in the personal goal revision process over time and results in a corresponding decline in the importance of assigned goals in the personal goal process. The mechanism by which goal calibration takes place in goal revision is argued to be Bayesian updating. This dissertation tests empirically whether goal calibration, through the mechanism of Bayesian updating, offers significant explanatory value of the personal goal revision process over time.

I begin my review of the relevant literature by discussing goal setting research and how assigned goals have their impact through personal goals. I then review the existing empirical work that finds that personal goals are often modified over time. Such goal revisions are found to be a function of feedback on goal discrepancies and previous performance experience. Next, I offer a theory to explain the goal revision process called goal calibration. Goal calibration is argued to take place through the mechanism of Bayesian updating. Then, hypotheses about personal goal revision that come from the goal calibration perspective are presented and tested. Finally, research results and their implications for personal goal revision theory are discussed.

Traditional Goal Setting Theory

The work of T. A. Ryan (1970) on intentional behavior informed early goal setting work. Early goal setting research looked to find inductively how assigned goals affected individual performance on a task (Locke, 1968; Locke & Latham, 1990). These studies examined the impact of specific goals of varying difficulties compared both to each other and to vague "do your best" goals or no goal conditions in varying tasks and durations (Locke, 1982; Locke &

Latham, 1990). The general trend of these studies was for specific and difficult goals to increase performance relative to less difficult, vague, or no goal conditions (Locke & Latham, 1990). These research studies lead to the publication of Locke and Latham's 1990 book *A Theory of Goal Setting & Task Performance,* which elaborates a general theory of goal setting.

In the book, Locke and Latham (1990) presented the strong existing meta-analytic empirical support for goal setting. Four meta-analyses examined the effect of goal difficulty on performance, finding effect sizes ranging from .52 to .82 of difficult goals increasing performance (Chidester & Grigsby, 1984; Mento, Steel, & Karren, 1987; Tubbs, 1986; Wood, Mento, & Locke, 1987). Five meta-analyses of the research area found effect sizes ranging from .43 to .80 for specific, difficult goals increasing performance compared to "do your best" or no goal conditions (Chidester & Grigsby, 1984; Hunter & Schmidt, 1983; Mento et al., 1987; Tubbs, 1986; Wood et al., 1987). These results suggest the effectiveness of specific difficult goals for increasing task performance.

Locke and Latham (1990) go on to discuss why conceptually specific and difficult goals are effective. One aspect is that such goals set a clear standard to attain, where success or failure is readily apparent. While the specific and difficult numerical goals give only one standard for success, more vague goals such as "do your best" goals let an individual pick a performance level that can be below the difficult goal an experimenter would set. A vague goal allows for an individual to have a range of values that they see as "good enough" in accomplishing the goal.

The view of Locke and Latham (1990), is that specific, difficult goals are more effective than vague "do your best goals" because for people in general the specific difficult goal is more difficult than the "do your best" goal and any self-standards that people might set from the "do your best" (i.e. deciding that one's best is equivalent to a specific numerical performance level).

Another aspect is that specific and difficult goals help people to know where to direct effort. High goal difficulty acts as a push factor for individuals to increase the effort they direct toward the task (Bandura & Locke, 2003). The goal lets them know where effort should be expended. Locke and Latham (1990) argued that the specific and difficult goals led people to invest more effort in task to accomplish the goal, leading to higher levels of performance.

Developing Goal Setting Theory

While Locke and Latham (1990) argued for the effectiveness of specific and difficult performance focused goals, limitations to such goals effectiveness and the primary focus on effort placed by Locke and Latham (1990) was found. In the meta-analysis of Wood et al. (1987), task complexity was examined as a moderator of the goal setting effect. All studies in the meta-analysis were rated by the experimenters as to the degree of complexity of the task used. The positive effect of specific and difficult performance focused goals was found to be stronger for simple tasks ($r = .77$) than for complex tasks ($r = .41$). Specific, difficult goals were more successful in simple tasks that focused on effort expended by participants than in complex tasks where participants needed to learn how to successfully engage in the task. Since learning is a major aspect of a wide number of important tasks, this presented a significant limitation of Goal Setting Theory.

Research also found situations where specific, difficult performance goals seemed to be detrimental to performance. The work of Earley, Connolly, and Ekegren (1989) found that "do your best" goals resulted in better performance in a stock price prediction task than a specific and difficult goal. The task was a multiple cue probability learning task (MCPL) with participants given various cues values that when weighted correctly in a formula would successfully predict the stock value that would result within a margin of error. Thus, participants needed to learn how the task worked to a significant degree rather than just expend more effort as was true for much of the earlier goal setting work (Locke & Latham, 1990).

Earley et al. (1989) found that in the stock prediction task the vague "do your best" goal resulted in better performance than the specific, difficult performance-focused goal. People with a performance goal were more likely to quickly change strategies than people with a "do your best" goal. Such behavior resulted in performance goal participants giving up on strategies before their value could be fully discovered. Earley et al. (1989) explained the effect by arguing that to be successful participants needed to develop a "meta" strategy for the prediction task and in doing so they would learn how the task worked and what weights were correct. People with a performance goal never developed this "meta" strategy and instead constantly changed strategies, hoping to find the strategy that would lead to reaching their specific and difficult performance focused-goal immediately. The difficult performance-focused goal put a pressure on participants to find the best strategy quickly and this resulted in them engaging in less task learning that was ultimately vital to success. In such a situation where the task needed to be learned, specific and difficult performance goals were a detriment to performance.

The weaker relationship strength for specific difficult performance-focused goals in complex tasks found in Wood et al. (1987) and the negative effects of such goals in work such as Earley et al. (1989) led to greater research attention on other types of goals. With tasks often having a learning and/or strategy choice component, an understanding of how goals worked in such task types was needed. Work in the educational research area on the types of goals people naturally set led to a new major type of goal being considered, the learning goal.

Work by Elliot and Dweck (1988) discussed the general tendency of individuals to engage in tasks with two basic types of goals: performance goals and learning goals. Performance goals focus people on trying to maintain positive judgments of their ability by performing at a high level. A performance goal is focused on an individual getting a high score on a task (Elliot & Dweck, 1988). This type of goal is basically the same as those used in traditional goal setting studies. A focus is placed on attaining a high score in the task, and thus performing at a high level (Locke & Latham, 1990). High performance is the desired outcome for a performance goal.

The second type of goal is a learning goal, which focuses attention on building competencies and mastering a task (Dweck & Legget, 1988). Individuals with a learning goal want to understand how a task works and master the skills needed for success. Such a goal focuses on mastering the task rather than performing at a certain level. Such goals could be more beneficial than traditional performance goals on complex tasks and tasks that require significant learning components, as learning how the task works can be crucial. In a task like the MCPL stock prediction task used in Earley et al. (1989), a learning goal would potentially have had a similar effect to the “do your best” goal, focusing attention on learning how the cues related to the stock price as opposed to a specific performance target. A number of studies have used learning goal manipulations and found them to be beneficial for increasing task performance in complex task and learning focused situations (Earley et al., 1989; Kozlowski & Bell, 2006; Seijts, Latham, Tasa, & Latham, 2004; Winters & Latham, 1996).

A meta-analysis by Utman (1997) examined studies which compared groups with learning or performance goals. In all studies included in the meta-analysis, experimenters manipulated the goals received by participants to either be performance or learning goals. Utman (1997) found a positive impact of learning goals on general task performance compared to performance goals with an effect size of $d = .53$. Utman (1997) went on to examine whether task complexity was a moderator of the relationship. All studies in the meta-analysis were rated in terms of task complexity by judges. A composite rating of task complexity was related to the effect size for each study, and the contrast was found to be significant and positive, $z = 2.22$, $p < .05$. The result means that as the rating of task complexity increased the learning goal advantage increased as well. Learning goal manipulations had an insignificant impact on task performance in simple tasks ($d = -.03$), but a large significant effect size on task performance in complex tasks, $d = 1.18$. Learning goals had a large impact on performance in complex tasks but no effect in simple tasks. These results taken as a whole suggest that learning goals are more beneficial in complex tasks than performance goals.

Since Utman (1997), greater knowledge has been generated about the effects of learning goals on task performance and learning, with research related to goal setting placing a greater focus on the need to examine how goals impact task learning and strategic choice. Work by Latham and a number of colleagues have attempted to show that specific and difficult goals are still the best means to increase performance even in complex tasks, with the difference being goals focused on specific learning outcomes rather than a specific task performance level (Seijts

& Latham, 2001; Seijts et al., 2004; Winters & Latham 1996). In each of the studies participants were asked to engage in tasks where multiple cues had to be taken into account and understood in order to perform well. They can be categorized as multiple cue probability learning task (MCPL) in the vein of the work of Earley (Earley, 1985; Earley et al., 1989). In their work participants are given goals that specify a number of strategies to develop or use within the task rather than a particular task performance level to obtain. Thus, the goals are specific and have a numerical referent but are focused on learning related elements rather than just high task performance scores. Such learning-focused assigned goals were found to have positive impact on task performance beyond normal performance goals (Seijts & Latham, 2001; Seijts et al., 2004; Winters & Latham 1996).

While the research area of goal setting focused initially on simple tasks and assigned goals impacting effort, it has developed to include learning and strategy development as a significant focus. As seen in the Earley et al. (1989) study and the work using learning goals (Dweck & Legget, 1988; Kozlowski & Bell, 2006; Winters & Latham, 1996) goals can have a significant impact on how people learn and what they attend to in a task to the benefit (or even detriment) of task performance. This dissertation focuses on the learning/strategy aspects over effort allocation aspects of goal setting. Now this dissertation turns to look at how assigned goals have their impact through the medium of personal goals.

Assigned and Personal Goals

One of the central assumptions in Goal Setting Theory is that for assigned goals to affect individual behavior they must be internalized (Locke & Latham, 1990). Locke and Latham

(1990) emphasize that in order for an assigned goal to have its full impact on performance it must be accepted. When an assigned goal is not accepted, the positive effect of an assigned goal on performance will be lessened or non-existent. Assigned goals must be accepted and translated into personal goals for them to be effective, with individuals consistently applying them over time. As discussed below, empirical research shows that when an individual does not do so, the effect of the assigned goal on performance is weakened or non-existent.

Erez and Zidon (1984) looked at the issue from the perspective of goal acceptance. Erez and Zidon (1984) gave participants a perceptional speed task over 7 trials, where in the experimental condition for each trial participants were given a new, more difficult goal. The goals started at very easy (probability of success = .9) to virtually impossible (p = .000). Performance level probabilities of success were based on a pilot study. Participants in the control group were just given a goal of "do your best," which was the same across all trials. Erez and Zidon (1984) had participants rate their degree of acceptance of their assigned goal before each trial.

Erez and Zidon (1984) found that the positive impact of a difficult assigned goal only held when the assigned goal was accepted. When the assigned goal was rejected and not followed, individuals in the assigned goal condition on average performed worse than the control group. When the assigned goal was not accepted by participants, performance was not helped and in fact decreased. These results offer support for the need of people to accept the assigned goal and make it their own for the assigned goal to be effective.

Work by Tubbs (1993) specifically looked at how the difference between the assigned goal and personal goal affected the assigned goal-performance relationship. Tubbs (1993) found that the difference between a person's assigned goal and personal goal moderated the relationship between the assigned goal and performance, with the greater the difference, the weaker the relationship. As the personal goal differed from the assigned goal, the positive performance effect of an assigned goal weakened. For assigned goals to affect performance they must be accepted and internalized when an individual sets a personal goal. The impact of the assigned goal on an individual's personal goal is the means by which assigned goals impact performance.

The Decaying Influence of Assigned Goals

While cross-sectional goal setting work has generally supported that individuals translate the assigned goal into a personal goal in cross-sectional experiments, empirical research that explores individuals performing tasks over multiple trials indicates that the impact of assigned goals on personal goals may decay over time.

For instance, research by Wood, Bandura, and Bailey (1990) found that over a number of trials, people with different assigned goals ultimately set similar personal goals, ignoring the assigned goals. Wood et al. (1990) asked participants to engage in a complex managerial decision-making computer simulation. Participants were asked to allocate workers to various tasks and offer various reward, goal, and feedback arrangements to each worker. Two assigned goal manipulations were used, a "do your best" goal and a high difficulty goal that was set at a level of performance equal to an amount only 5% of participants had obtained in previous administrations of the task (Wood & Bailey, 1985). Participants were asked to make numerical self-set goals after the fourth and twelfth trials of the experiment (Wood et al., 1990).

Contrary to researcher expectations, participants in both conditions set goals of a similarly challenging level at both time points (Wood et al., 1990). A general downward trend over time in personal goal level was also found. As participants engaged in the task repeatedly, they revised their goals downward. While their assigned goals had not changed, the task related experiences and previous performance information gained over time influenced them to revise their personal goals. By the time of measurement after trial four, personal goals were not impacted by assigned goals. The similar experiences and performance levels in the task led participants to set similar personal goals even if their assigned goals differed. These results offer strong evidence for decay over time of the impact of assigned goals on personal goals.

Similarly, work by Tubbs, Boehne, and Dahl (1993) focused on predicted performance, and their results suggest a decay of importance of the assigned goal over time. They found that initial levels of predicted performance differed based on the assigned goal. Individuals with a difficult assigned goal had higher predicted performance levels than those given an easy goal. Once participants actually engaged in the task, however, Tubbs et al. (1993) found no significant differences in predicted performance between the two assigned goal groups. Once actual performance information was gained, information likely to be similar for each group, individuals began to modify their predictions of performance to fit those actual performance levels. Actual task performance informed their beliefs about predicted performance, rather than assigned goals, as the task progressed.

In Tubbs et al. (1993), personal goals were measured but not analyzed directly. Looking at the personal goals set, they were closer to assigned goals initially than they were in later trials, when feedback was available. For the difficult assigned goal of 45, participants set personal goals very similar to the assigned goal, the mean being 44.47. After performing the task and on average only scoring 24.87, however, the average personal goal set fell to 38.20. On average, personal goal revision took place after trial 1 performance did not meet the trial 1 goal. A similar pattern was found with the easy goal condition, as participants moved upward in their personal goals away from an easy goal of 15 as they performed the task over four trials. The actual task performance experiences informed the personal goals they set.

Finally, research by Meyer and Gellatly (1988) did not look directly at the issue of assigned goal effects on personal goals over time, but did look at how task-related data affected the assigned goal's impact on predicted performance. They examined how performance norm data affected the assigned goal effect on predicted performance, finding the relationship was greatly attenuated when norm data was given. In the absence of norm data, assigned goals had a major impact on predicted performance, suggesting the assigned goal was used to help determine what level of performance was attainable. Assigned goals were used to predict future performance. When norm data was given, however, individuals used that data as well to determine predicted performance, weakening the assigned goal's impact on predicted performance. While this does not directly examine the assigned goal-personal goal relationship, previous performance could be seen as having a similar function to norm data. Previous performance can act as personal norm data on how that individual performed in the past and thus is likely to perform in the future. In Meyer and Gellatly (1988) norm data was found to weaken the effect of assigned goals on predicted performance and it might be expected that the norm data related to personal previous performance affects other assigned goal relationships, such as the relationship with personal goals. Previous performance gives information on what an individual is likely to obtain in the future and this could influence the personal goal set.

Discrepancies and Personal Goal Revision

Research that has examined goal revision from initial personal goal level offers some additional illumination on how an initial goal might be modified over time as a function of task experience. One major mechanism suggested in this process is the discrepancy between a personal goal and actual task performance. In both major theories of goal directed behaviors over time, Control Theory and Social Cognitive Theory, goal-performance discrepancies are central. In Control Theory individuals are focused on discrepancy reduction, reducing the difference between actual output and the goal level of output from a standard or goal (Lord & Levy, 1994). In Social Cognitive Theory individuals engage in both discrepancy creation and discrepancy reduction. Individuals set goals for themselves above current performance levels, creating goal discrepancy. They then work toward those goals and thus engage in goal discrepancy reduction (Bandura, 1991). As they get closer to achieving a goal, they increase the goal to a new, higher level, creating a new discrepancy. As such, discrepancies are continually created and reduced over time as a function of new personal goals and increases in performance level.

Research has examined the degree to which people engage in goal discrepancy creation and goal discrepancy reduction. People have been found to engage in both, although the incidence rate of goal discrepancy reduction has been generally found to be significantly larger (Campion & Lord, 1982; Donovan & Williams, 2003; Phillips, Hollenbeck & Illgen, 1996;

Scherbaum & Vancouver, 2010). People often are looking to reduce these goal-performance discrepancies. Why this is the case is built into both goal directed behavior models.

Both Social Cognitive Theory and Control Theory have an inherent assumption that discrepancies are unpleasant. In Control Theory individuals work to reduce goal discrepancies with discrepancies seen as unpleasant, resulting in negative affect (Lord & Levy, 1994). In Social Cognitive Theory, attainment of a goal level allows for positive self-evaluation and positive affect (Bandura, 1991). Lack of goal attainment, however, forestalls positive evaluation and can lead to a despondent mood when a discrepancy is seen as insurmountable (Bandura, 1991). In Social Cognitive Theory, positive feelings result with attainment of a goal or when the discrepancy has been greatly reduced, not as a function of having a discrepancy. A person feels good because they have reduced a discrepancy or reached a goal, not because of the state of having a goal discrepancy.

Both perspectives posit discrepancies as inherently unpleasant, potentially causing negative affect or dissatisfaction. In failing to reach the desired goal or make reasonable progress toward the goal, people are dissatisfied with the result. Discrepancies have generally been conceptualized as causes of negative affect, especially when sufficient reduction of such discrepancies is seen as unlikely to occur in the future (Carver & Scheier, 1990).

Discrepancies can also lead people to doubt their task-related competencies (Bandura & Cervone, 1983). A discrepancy suggests an individual does not have the task related skill to reach the goal level of performance. In such a situation an individual needs to reconsider his/her existing assessment of personal skill and the attainability of a goal in light of actual performance (Bandura, 1991). Discrepancies have potentially negative consequences for individuals in terms of affect and perceptions of personal competency, and thus, it is expected individuals will strive to avoid discrepancies.

The unpleasantness of goal-performance discrepancies leads individuals over time to search for a means of reduction. An individual has two major means to reduce the discrepancy: either by changing task related behaviors (such as task-related effort) or by revising the goal (Bandura, 1986; Lord & Levy, 1994). For a large enough discrepancy an individual may not see a way of changing task behaviors or effort to significantly reduce the discrepancy. In the case of a task done repeatedly over time, consistent performance below a goal level suggests that changing effort or other task behaviors will not decrease the discrepancy. As such, it is expected that the greater the discrepancy and the number of repeated instances of having the discrepancy, the greater the personal goal revision to decrease the discrepancy. This relationship has received empirical support.

Work by Campion and Lord (1982) examined how students in a psychology class changed their personal goals for the next test and their course grade as they actually took tests and the semester progressed. Looking at goal changes from test to test, they found that people who scored below their target grade for the test were more likely to lower their grade goal on the next test. This effect was also more likely when participants were two or more grade levels below their target test goal and/or after having multiple failures at that goal level. Discrepancies led to personal goal revision from the initial goal (Campion & Lord, 1982). The actual tests taken, and the goal discrepancies found between their grades and the initial goal, led to personal goal revision. Students used test performance information to set goals that would result in smaller discrepancies, regardless of whether such revision caused them to deviate from initial goals. Assigned goals might be viewed as more salient than initial goals, but it seems quite likely the basic revision process would be similar.

Work by Donovan and Williams (2003) looked at such relationships more directly using a within person analysis design. They looked at the personal goals set by varsity track and field athletes for a track season and how those goals were revised over time from initial goal levels, based on actual performance and goal-performance discrepancies. They found that an individual's level of goal-performance discrepancy predicted the amount of goal revision downward, such that larger discrepancies led to greater downward goal revision (Donovan & Williams, 2003). They found this effect was more pronounced in the second half of the season as well. As more previous performance information was gained over time, that information had a greater impact on goal revision. Significant discrepancies led individuals to deviate from initial goals, revising personal goals to have smaller goal-performance discrepancies (Donovan & Williams, 2003). Actual previous performance from track meets became influential in the personal goals set, causing people to change their personal goals from their initial personal goal levels. Such results show the importance of previous performance in the personal goal creation process.

While research has shown the tendency of individuals to revise goals downward over time when there is significant negative goal discrepancy, how individuals react to positive goal discrepancy (i.e. performance at or above an existing goal) is still relatively unclear. In the work of Phillips et al. (1996) some high performers upon reaching or exceeding their goal did not increase their goal, rather they kept it static. Phillips et al. (1996) suggested this could be due to high performers deciding that the current level of performance was acceptable and did not need improvement. Looking to the results of Campion and Lord (1982), as well as Donovan and Williams (2003), it seems possible that this was a result of those high performing participants determining that they were already near the top level of potential performance. Previous performance information may have informed them that progress toward a higher goal level was unlikely. The decision to keep a current goal upon attainment or set a new, higher one could be significantly informed by previous performance and how such information predicts likely future performance.

Taking these studies as a whole, when considering what influences an individual's personal goals, there are two major influences: assigned goal level and previous performance. When an individual is preparing to engage in a task for the first time the only task information they possess is often the assigned goal level. As was shown in Tubbs et al. (1993) and Meyer and Gellatly (1988), such information can greatly inform what performance an individual predicts he/she will achieve. An individual does not have previous performance information when he/she is just starting a task, and the assigned goal is one of the only things that he/she has on which to base a personal goal. Thus, for an initial task instance, an individual's personal goal would be expected to be greatly impacted by the assigned goal.

For subsequent personal goals, however, an individual has previous performance information as well. This information informs him/her how he/she has done before and how he/she might be predicted to do in the next performance instance. Previous performance informs future performance prediction and, as such, should influence the personal goal set. Previous performance gives future predicted performance information that can be used to create a personal goal that will not result in large goal-performance discrepancies and the unpleasant affect/cognitions they can bring (Carver & Scheier, 1990). Thus, personal goals should follow predicted performance levels, lessening such discrepancies. With previous performance having a greater impact, the impact of the assigned goal will be lessened. As such, assigned goals should have greater impact on the initial personal goal and early trial personal goals, while previous performance has a greater impact as an individual gains more previous performance instances.

While such a perspective is inherently valuable in deepening our understanding of the personal goal setting process and how assigned goals impact personal goals, in itself it gives no information on exactly how such a process unfolds over time. A perspective that can explain how such a personal goal process occurs over time is goal calibration, with Bayesian updating the mechanism by which the process unfolds over time.

Goal Calibration

Goal calibration offers an explanation of how personal goal revision progresses over time, building on existing empirical and theoretical knowledge in the personal goal setting literature. Inherent in this view is that the information a person possesses and is able to use in the personal goal setting process changes over time and task experience. The goal calibration perspective argues that individuals use the relevant information they have available to determine what personal goal they should set or revise at any given point in performing a task.

In the personal goal setting and revision process, the first time point of goal calibration is right before an individual engages in the task for the very first time. When individuals begin a novel task, they may have little to no knowledge about how they will perform. As such, the values for their initial personal goal can be very tentative and open to revision over the first few trials as performance information is gained. When starting a task, an individual has limited information with which to determine what is a reasonable personal goal to set, but must use that limited information to set a personal goal that makes sense. Individuals calibrate their personal goal based on the information they have.

In the setting of an initial personal goal, one potentially significant information source for its value is an assigned goal. In experiments with novel tasks, participants are often given an assigned goal to strive for by the experimenter (Locke & Latham, 1990). Since participants might see the experimenter as knowledgeable about the task and what type of performance is possible, the assigned goal is likely to be influential in the decision of what the first personal goal should be. This could lead the participant to adopt the assigned goal directly as their a priori goal. If the participant has had any practice on the task, or seen a demonstration of the task, that information could also play a role in determining that initial a priori personal goal. As such, the initial a priori goal should be heavily influenced by these factors.

When an individual does a task repeatedly over time, he/she accumulates performance information and task-related experiences. This knowledge gained from previous performance increases an individual's understanding of what performance is likely to happen in the future and what levels of performance are possible. Such knowledge should have a strong influence on personal goal levels. Evidence for this is found in empirical within person work, as over time initial goals are revised downward toward actual performance levels (Campion & Lord, 1982; Donovan & Williams, 2003).

As previously mentioned, during the initial personal goal setting phase the assigned goal is one of the only sources of information about the task and thus would be expected to have a major impact on the personal goal set. As an individual gains previous performance information as described above, he/she gains increased information with which to calibrate what personal goal is set. The individual has a clearer understanding of what performance is likely and, as such, goal calibration predicts that assigned goals become less salient in personal goal setting over time while previous performance becomes more salient. Previous performance allows individuals to more closely calibrate personal goals with predicted future performance, reducing the unpleasantness that can come from performance-goal discrepancies (Carver & Scheier, 1990). It is proposed that the mechanism by which the goal calibration process takes place is Bayesian updating. I will now turn to an explanation of Bayesian updating and research that suggests it is a process inherent to how humans engage in cognition.

Bayesian Updating and Human Cognition

Bayesian updating is a process that makes predictions of future outcomes by modifying previous or a priori predictions to take into account previous outcomes and the variance of those outcomes. Such a process begins with an initial estimation of the value of a future outcome for a task. As the task is performed over time, the information from each performance is then used to modify the predicted outcome level for the next task performance instance. This fits well with the goal calibration perspective, and Bayesian updating is proposed as the mechanism by which goal calibration proceeds.

Research and theory has supported the concept that humans naturally engage in Bayesian processes in cognition. Peterson and Beach (1967) conceptualized humans as intuitive statisticians. They reviewed the existing literature of the time comparing human cognition and optimal Bayesian processes and found support that individuals engaged in similar estimation processes, although the values they came up with were not always exactly the same as optimal Bayesian predictions. While the predictions were not perfect, the methods being used by participants were consistent with those of statistical probability and Bayesian theory (Peterson & Beach, 1967). Ensuing empirical and theoretical work has built on this insight, modeling and finding support for Bayesian updating and estimation processes across a range of human cognitions. For one example, work by Steyvers, Tenenbaum, Wagenmakers, and Blum (2003) examined human models of causal inference from a Bayesian theory approach and found that while errors were made from optimal Bayesian predictions, the basic approach used by humans fit Bayesian Theory. For another example, research by Oaksford and Chater (2001) found that a Bayesian perspective had explanatory value for the cognitive processes that are involved in symbolic reasoning. This significant body of work suggests that individuals naturally use Bayesian methods when engaging in a number of cognitive processes.

An example especially germane to the estimation of future outcomes is research by Griffiths and Tenenbaum (2006). They found empirical support for individuals making predictions of duration/amount for a number of variables in a way consistent with a Bayesian approach. Participants were asked to make predictions on a number of everyday variables, such as final movie grosses, poem lengths, life spans, movie run times, U.S. representatives' terms, cake baking times, and Egyptian pharaoh reigns (Griffiths & Tenenbaum, 2006). Each of these variables represents likely areas that participants had previous experience with in everyday life. Thus, for such predictions, participants had existing a priori beliefs based on everyday experiences with such variables.

Griffiths and Tenenbaum (2006) took participant responses and compared them to optimal Bayesian predictions. To do so, they examined data sources on the true distributions of the variable and used them in Bayesian equations. They found that participant judgments for life spans, movie run times, poem lengths and terms of U.S. representatives were indistinguishable from optimal Bayesian predictions, and baking times was close to the ideal despite having an irregular distribution. Thus, they found support for participants following a Bayesian model of prediction for all those variables.

For the variable of lengths of pharaohs' reigns, participants had the correct prior distribution shape but had estimates that were too high. Griffiths and Tenenbaum (2006) examined why this was the case, finding participants had an estimated average reign length that was too high compared to actual pharaoh reign durations. When the optimal Bayesian equation used the actual prior reign length beliefs held by participants, participants' predictions had a close correspondence to the optimal Bayesian prediction (Griffiths & Tenenbaum, 2006).

Griffiths and Tenenbaum (2006) offer strong evidence for humans engaging in Bayesian updating when making predictions in everyday life. The study suggests that when a person has accurate prior information they make predictions that fit optimal Bayesian predictions. Prior information is used in a way consistent with Bayesian theory. Overall, the Bayesian cognition literature base offers strong support for Bayesian principles underlying the prediction process for humans. While the literature base has looked at a number of cognitive processes, one area of particular salience has been ignored- personal goal revision. I will now explain how Bayesian updating fits with personal goal revision decisions.

Personal Goal Revision as Bayesian Updating

The Bayesian cognition approach has clear explanatory value applied to personal goal setting. As discussed previously, it has been shown empirically that individuals use previous task performance to inform how they revise goals (Campion & Lord, 1982; Donovan & Williams, 2003). They change personal goals to fit with this task related information that they have gained, using such information to predict what performance levels are attainable and to set personal goals that don't create large goal-performance discrepancies.

Bayesian updating offers an excellent fit with the personal goal revision process described above, as the initial prediction maps onto one's initial goal, and the future outcome prediction process maps onto the personal goal revision process affected by previous performance as described above. Assigned goals could be seen as the information that informs the initial or a priori goal/prediction in the Bayesian updating process. Bayesian updating offers a powerful perspective with which to understand personal goal revision. The work of Griffiths and Tenenbaum (2006) also suggests individuals naturally use a Bayesian updating approach when making predictions and it seems likely such a process would be involved in personal goal setting as it includes a prediction element. Now discussion will turn to the mathematics of Bayesian updating.

Mathematical Base of Bayesian Updating

Bayesian updating was built out of a deceptively simple rule of probability called Bayes' Rule. Bayes' rule is an equation by which one can calculate the conditional probability of a variable *b* given variable *a* when one knows the conditional probability of *a* given *b* and the probabilities of each variable (Bayes, 1763/1958). The likelihood of a certain value or instance is calculated using information on the likelihood of the outcome of interest and the likelihood of having the given value for the other variable (Griffiths, Kemp, & Tenenbaum, 2008). For a more concrete example, Bayes' rule could be seen as a rule showing that a probability of a hypothesis B, given observed evidence A, is based on the inverse of that relationship (i.e. the probability of evidence A given hypothesis B) and the respective probabilities of A and B. The basic equation is:

$$p\ (B \mid A) = p\ (A \mid B) * p\ (B) / p\ (A)$$

Thus, in words, the equation is stated as the probability of B given A is equal to the probability of A given B multiplied by the probability B and then divided by probability A (Griffiths et al., 2008). Thus, the probability of a hypothesis B given A is calculated using the probabilities for each variable (the hypothesis and the evidence) and the inverse relationship (evidence given the hypothesis).

While the rule itself is relatively basic in probability theory, its implications can be significant. Bayes' rule allows for the calculation of a posterior probability after evidence has been accumulated (Griffiths et al., 2008) This means that Bayes' rule can be applied to change and correct probability estimates as new evidence accumulates, as well as be used to compare probabilities of various outcomes based on evidence gained. For example, in the case of a medical diagnosis, given a symptom like elevated temperature, the probability a person has a range of possible diseases can be calculated to determine the most probable disease possessed.

Bayesian Updating Basic Elements

While Bayes' rule can be used in determining the probability of a hypothesis given evidence, more complex models are needed for many real world situations. For instance, predictions may be made over time and across task occurrences. As formulated, Bayes' rule does not take advantage of the greater certainty that can come over multiple prediction and evidence points. As an outcome is observed over time, a clearer idea should be gained of what that outcome is likely to be and how it varies, making later information less impactful. In order to take such over time variables into account, the more complex equations of Bayesian updating are needed.

Bayesian updating allows for a prediction to be updated over time as a function of output and variance to make more accurate predictions of future output. It can also be used to model situations where the level of production can vary systematically or unsystematically over time (ex. a task where increased experience at the task generally leads to higher levels of mean performance).

The Bayesian updating process involves making a predicted output level for the next performance of a task. To do so, the prediction for the previous output level is modified by the discrepancy between that prediction and the actual output attained, which is weighted by a factor called the Kalman gain. The Kalman gain is a weighing term that takes into account the variance of the process and amount of previous output occurrences (Petris, Petrone, & Campagnoli, 2007). In general, the weighing factor results in new output instances being given less weight the more previous output instances there are and/or the lower the variance of the process.

Bayesian Updating Equations- Static Case

Bayesian updating can be used in a number of different cases where predictions of future output are needed. The most basic prediction type is in the static case, where systematic change in the output level is not expected over time. While the actual production level may have variability in output, in the static case this variability is expected around a mean level of performance with variance in outputs being the reason for differing individual output levels. The equation for Bayesian updating in the static case is:

$$m_n = m_{n-1} + (C_{n-1}) / (C_{n-1} + \sigma^2) * (y_n - m_{n-1})$$

In this equation m_n represents the prediction of output for the next output instance. m_{n-1} represents the prediction of output for the previous output instance. y_n represents the last output level. The difference between the previous output level and the previous prediction is calculated, called the discrepancy in prediction. $(C_{n-1}) / (C_{n-1} + \sigma^2)$ represents the Kalman gain, the weighing factor of that discrepancy. In the Kalman gain, C_{n-1} represents the previous estimation of variance, with σ^2 being equal to that actual variance. The calculation of C_n will be described in the next equation. The equation states that the next predicted output level is equal to the previous output prediction added to the discrepancy, with the discrepancy weighted by the Kalman gain. Thus, in the Bayesian updating process, new predictions are influenced by previous prediction discrepancies, with the impact of the most recent prediction discrepancy determined by the Kalman gain value.

The variance estimation value also changes for each output prediction. It changes as a function of the actual variance. The full equation is:

$$C_n = (\sigma^2 C_{n-1}) / (\sigma^2 + C_{n-1})$$

In this equation C_n is the current estimation of variance. C_{n-1} is equal to the estimation of variance for the previous output instance. σ^2 is the actual variance in outputs for the process being examined. Thus, in calculating the current estimation of variance (C_n), the previous estimation of variance and the variance of the sample are taken into account. In general, as more output instances happen, the Kalman gain value will become smaller, making new information weighted less in determining the new prediction value.

While both equations work for most performance instances, when a process begins, a priori values must be estimated. Systems using Bayesian updating need to set an a priori predicted output level for the first output instance (m_0) and an estimate of the variance of performance in the task (C_0). These two estimates become the base by which future output information from the process is used to modify these values in future trials to create more accurate output estimates and variance estimates. The variance of the task is crucial in determining how much a prediction should be modified, as it suggests how likely a new output level could have happened simply by normal variance around a task output mean, rather than an actual change in output level due to things such as mechanical failure, learning effects etc.

The decision process for deciding on these initial values can differ greatly based on the information available. For standardized machines, an initial prediction level might be tied to manufacturer's data on production levels. It could also be generated based on a test run of the task. As such, the precision of this initial prediction of output can vary greatly based on the information available.

The prediction of variance has similar concerns. In the absence of information on expected variance, the initial estimate of variance is likely to be very high, so that the potential variance in output is not underestimated. In most cases this initial variance estimate will become a much smaller value once the task is performed and actual variance information is gained.

Bayesian Updating Equations- Dynamic Case

The equations presented previously are for the situation where the actual level of production is believed to remain relatively static, with no expected systematic or unsystematic change. In the case where dynamic changes are expected, such as a machine becoming more productive as it is broken in or a person performing better with more experience, the equation requires some modification.

Two additional terms need to be utilized in calculating a prediction through Bayesian updating in a dynamic environment. The first term involves updating the previous prediction of output by the average change in mean performance per output occurrence (Petris et al., 2007).

For instance, a person might get two points better on average every time they perform a certain task. For the Bayesian updating prediction to be as accurate as possible, this increasing quality of performance must be taken into account. The basic equation for this term is below:

$$a_n = m_{n-1} + v$$

In the equation a_n represents the previous prediction updated by the predicted average increase per additional trial. m_{n-1} represents the previous predicted output. The variable of v represents the mean change in output from output instance to output instance (Petris et al., 2007). This term can take more complicated forms based on the type of change in the output over time. Thus, this equation provides a predicted output value updated based on the expected change in output from trial to trial.

The second additional equation involves modifying the variance prediction value to take into account the variance of the change in performance from trial to trial in the case of dynamic change. The equation is:

$$R_n = C_{n-1} + \sigma^2_w$$

The term R_n represents the previous variance estimation adjusted by the variance associated with the change in mean output level from trial to trial. C_{n-1} is the variance estimation value of the previous output trial. σ^2_w represents the variance associated with the change in output from trial to trial (Petris et al., 2007). So the equation as a whole involves updating the previous variance estimation to account for the variance related to the change in predicted output due to an added trial.

The equations for the new predicted output level and variance estimation in the dynamic case are similar to those in the static case, except for the two values calculated above are used to take into account that the average output level is changing over time. The basic dynamic Bayesian updating prediction equation is:

$$m_n = a_n + (R_n) / (R_n + \sigma^2) * (y_n - m_{n-1})$$

The major change in the equation between static and dynamic is a_n replacing m_{n-1} at the beginning of the equation and R_n replacing C_{n-1}. For both cases this is done to take into account the changing level of output from trial to trial (Petris et al., 2007). The equation as a whole states that the next predicted output level is equal to the previous output prediction adjusted by the changing level of output from trial to trial added to the discrepancy, with the discrepancy weighted by the Kalman gain.

The predicted level of variance is changed in a similar way, with the calculated R_n replacing C_{n-1} in the equation:

$$C_n = (\sigma^2 R_n) / (\sigma^2 + R_n)$$

The prediction of variance is now made to take into account the increased variability caused by the average output level changing over time (Petris et al., 2007).

Personal Goal Revision Process with Bayesian Updating Equations

I will now show how personal goal-setting can be applied to the Bayesian updating process and the related equations. In most cases the personal goal setting process will take place in a dynamic, rather than static environment and as such, the dynamic equations will be used. In most situations, in both lab and field settings, it is expected that there will be some learning or practice effects. As such, performance should get better over time generally, and the Bayesian updating equation needs to take that into account.

The first step before the task begins for individuals using Bayesian updating in the personal goal setting process, would be to set an a priori predicted performance level for the first trial (the initial personal goal) and an estimate of the variance of performance in the task (C_0). These two estimates become the a priori base by which future performance information from the task is used to manipulate and modify these values in future trials to create more accurate performance estimates and task performance variance.

When individuals begin a novel task they have little knowledge about how they will perform or their future variability of performance. Due to this the values for predicted performance (the initial personal goal) and predicted variance are likely to change significantly over the first few trials as performance information is gained. A significant information source for the value of the initial personal goal is an assigned goal. In experiments with novel tasks, participants are often given an assigned goal to strive for by the experimenter (Locke & Latham, 1990). Since participants might see the experimenter as knowledgeable about the task and what type of performance is possible, the assigned goal is likely to be influential in the decision of what the first personal goal should be. This could lead the participant to adopt the assigned goal directly as their a priori goal. If the participant has had any practice on the task or seen a demonstration of the task, that information could also play a role in determining that initial a priori personal goal. As such, the initial a priori goal should be heavily influenced by these factors.

Almost no information is likely to be known about the variance structure of performance for the task at the participant level before it has begun. As such, the initial estimate of variance is likely to be very high, so that the potential variance in performance is not underestimated. In most cases this initial variance estimate will become a much smaller value once the task is performed and actual variance information is gained.

So the first step of Bayesian Updating in goal-setting happens before a task begins, as individuals set two initial estimates: an initial personal goal (predicted performance) and variance of task performance (C_0). The later updating after the first trial will be updating and modifying these values to create a more accurate estimation for the second trial based on actual task experiences.

Once the initial personal goal and prediction of variance in task performance is made, individuals engage in the actual task in the first trial. By engaging in the task, individuals gain actual personal performance data and information on the variance of performance in the task. This information will be used in modifying the initial estimates of personal goal and variance in the Bayesian updating process for the personal goal used going into the second trial.

As previously discussed in the general description of dynamic Bayesian updating, first updates will be made to the previous prediction (personal goal) and variance based on changes in mean performance (here it could be due to a learning effect):

$$a_n = m_{n-1} + v$$

In the equation a_n represents the previous goal updated by the expected increase in performance by practicing one additional trial. m_{n-1} represents the previous personal goal. The variable of v represents the mean change in performance from trial to trial (Petris et al., 2007). Thus, this equation provides a predicted performance value updated based on the expected change in performance from trial to trial due to factors such as learning or a practice effect.

The second equation involves modifying the variance value to take into account the variance of the change in performance from trial to trial in the case of dynamic change. The equation is:

$$R_n = C_{n-1} + \sigma^2_w$$

The term R_n represents the previous variance estimation adjusted by the variance associated with the change in mean performance from trial to trial. C_{n-1} is the variance estimation value of the previous performance trial. σ^2_w represents the variance associated with the change in task performance from trial to trial (Petris et al., 2007). So the equation as a whole involves updating the previous variance estimation to account for the variance related to the change in predicted performance due to an added trial of task experience.

The equations for determining the new personal goal and new estimate of variance in this dynamic case then use the two values calculated above to take into account that the average performance level is changing over time. The dynamic Bayesian updating prediction equation is:

$$m_n = a_n + (R_n) / (R_n + \sigma^2) * (y_n - m_{n-1})$$

The equation as a whole states that the next predicted performance level (i.e. one's next personal goal) is equal to the previous personal goal adjusted by the changing level of performance from trial to trial added to the discrepancy, with the discrepancy weighted by the Kalman gain.

The predicted level of variance is:

$$C_n = (\sigma^2 R_n) / (\sigma^2 + R_n)$$

The prediction of variance now takes into account the increased variability caused by the average performance level changing over time (Petris et al., 2007). The changing in mean performance due to effects such as learning or practice, results in greater variance, which is reflected in this dynamic Bayesian updating equation.

Alternative Models of Personal Goal Revision Over Time

While this dissertation argues that a goal calibration model will best explain personal goal revision over time, existing alternative models also offer explanations of personal goal revision over time. This dissertation tests the goal calibration against two such models in examining which model best explains the personal goal revision process. The alternative models that are examined are a Goal Setting Theory model and a constant growth model. They will each be explained in turn.

Model 1: Goal Setting Theory model. As has been previously discussed, the dominant way personal goals have been examined is by the Goal Setting Theory of Locke and Latham (1990). The goal-setting approach has focused on how people with different assigned goals perform differently in a task situation. Little focus has been placed on how such goals might be implemented or used over time.

While there is little explicit description of how goals function over time in the goal-setting model, the mechanisms by which goals are effective offers information on how such goals should unfold over time. The central assumption in Goal Setting Theory is that for assigned goals to affect individual behavior they must be internalized and accepted by the individual (Locke & Latham, 1990). What this functionally means is that the personal goal strived for should match the assigned goal given. When the personal goal deviates from the assigned goal it is seen as lowered goal commitment and leads to a lessened impact of the assigned goal (Locke & Latham, 1990; Tubbs, 1993). Thus, from a Goal Setting Theory perspective as long as an individual stays committed to an assigned goal the personal goal should stay constant at the assigned goal value. Goal Setting Theory, therefore predicts that individuals will keep at a constant goal level over time, which is equal to the assigned goal value. This offers a very different prediction for personal goal revision over time than the model offered by goal calibration.

Model 2: Constant growth model. One of the most basic models of changes by an individual over time is the individual growth curve model. In a constant growth model a straight line growth model is posited, with an individual's value of an outcome changing consistently over time (Rogosa, 1995). Each individual has a unique value of the rate of growth over time. While such a model may be relatively simple, such models have been found to be useful in modeling actual growth processes over time (Hui & Berger, 1983; Rogosa & Willet, 1985). The basic equation used is:

$$\eta_{ip} = \eta_{1p} + \Theta_p(t_i - t_1)$$

In the equation the current level of an output is determined by the initial level added to the constant rate of change value multiplied by the number of time points that have passed since the initial time point. Thus, over time the value of an individual's outcome changes as a result of time passed and the person's individual rate of change.

Applied to the personal goal revision process, the constant growth model would predict that an individual changes his/her personal goal over time at a rate unique to that individual, with that rate remaining constant over time. Thus, one individual might slowly increase his goal over time while another individual might decrease his goal more quickly over time. Instead of being informed by task related information, an individual makes changes based on an individual's characteristics. This process is much different than the one proposed by goal calibration. In goal calibration that proceeds through Bayesian updating, all individuals would revise goals in similar ways, incorporating task performance information in determining the next personal goal set. In a constant growth model the rate of goal revision over time would be unique for each individual and would proceed at a constant rate of change for each individual.

Summary and Hypotheses

Comparing personal goal setting models. Existing evidence supports the idea that personal goal revision proceeds in a manner consistent with goal calibration by a Bayesian updating process, rather than either a Goal Setting Theory model or a constant growth model. In the personal goal setting process, an individual makes decisions about what goal he/she should set for the next trial. In setting a personal goal, the individual considers what goal level is reasonable and potentially attainable. In determining what goal to set, a person is influenced by the previous performance instances they have had, as well as the discrepancy between the previous personal goal and actual performance, as shown in the over time goal setting work of Donovan and Williams (2003), and Vancouver et al. (2001). People work to avoid large performance-goal discrepancies due to their emotionally unpleasant nature (Bandura, 1991; Carver & Sheier, 1990; Lord & Levy, 1994). To avoid such negative discrepancies, the personal goal setting process involves an individual making a prediction of what performance they are likely and/or able to obtain in the next trial. An individual's personal goals over time then should converge to the expected performance point, allowing him/her to avoid unpleasant discrepancies.

The work of Griffiths and Tenenbaum (2006) suggest that when individuals make predictions of future outcomes they use a Bayesian perspective. Predicted future outcomes are based on their experiences with the variable. For instance, knowledge of how most movies perform in terms of box office receipts, i.e. the known prior distribution, has a strong impact on what a person's prediction of a movie's ultimate box office take will be. When making such predictions, individuals make close to optimal Bayesian predictions.

With Bayesian theory having a major impact on how humans make predictions, it is a natural fit as the mechanism by which goal calibration affects personal goal setting decisions. When an individual does a task repeatedly over time, he/she accumulates performance information and task-related experiences. For the processing of such information in making personal goals, Bayesian updating is a logical choice, and one that is supported by the prediction results of Griffiths and Tenenbaum (2006). Bayesian updating allows for proper weighing of this information acquired, making the personal goal set a more accurate prediction of future performance, avoiding unpleasant goal-performance discrepancies. Goal calibration with a backbone of Bayesian updating for prediction offers an over arching theory to explain the empirical personal goal setting results found by Campion and Lord (1982), Donovan and Williams (2003) and Vancouver et al. (2001). Also, the empirical work of Griffiths and Tenenbaum (2006) suggests that people naturally engage in optimal Bayesian prediction for everyday predictions, suggesting Bayesian updating is likely to be a major mechanism in personal goal-setting due to personal goal setting's inherent nature as a prediction of future performance. Neither Goal Setting Theory nor the constant growth model account for individuals weighing information in such a manner. As such, it is hypothesized that:

Hypothesis 1: An individual's personal goal revision processes over time will better fit a goal calibration model through the mechanism of Bayesian updating than a Goal Setting Theory Model.

Hypothesis 2: An individual's personal goal revision processes over time will better fit a goal calibration model through the mechanism of Bayesian updating than a constant growth model.

Impact of assigned goals on personal goals. One of the bedrock assumptions of goal-setting work has been that people generally accept and commit to their assigned goals (Locke & Latham, 1990). This would functionally mean that the personal goals are set at the assigned goal level and that goal level is followed throughout the course of an experiment or performance type. Work that has looked at personal goal revision processes within individuals over time, however, has generally found that personal goals are often changed and revised from initial goal levels based on information gained over multiple performances such as previous performance and goal discrepancies (Campion & Lord, 1982; Donovan & Williams, 2003; Vancouver et al., 2001). This represents a conflict point between Goal Setting Theory and empirical goal revision research on how assigned goals are used and translated.

The Bayesian updating perspective offers some potential illumination on the issue. When starting a task and setting a priori goals or performance predictions, assigned goals are often one of the only pieces of information a participant has. As such, it would be expected that for initial or a priori goals, assigned goals are a major influence. Thus, initial goals are likely to be more clearly aligned with assigned goals.

Once participants begin to gain experience in the task and actual performance scores, however, Bayesian updating processes will revise those initial personal goals to align with actual performance instances. As such, while one would expect people with different assigned goals to differ in their a priori or initial personal goals, the similar performance levels and experiences participants have across assigned goal levels will lead to a convergence of similar personal goals based on this similar information. As such, it would be reasonable to expect assigned goals will be more important predictors of personal goal level early in a task than late, when actual performance information is likely to predominate. It is predicted that:

Hypothesis 3: Assigned goals will have a more pronounced effect on personal goal levels early in a series of occurrences of doing a task rather than later in the series.

Individual difference effects on goal calibration. While individuals should generally follow the goal calibration process over time it also seems plausible that individual difference factors could impact how closely the goal calibration process is followed. Individual difference factors have been shown to affect a wide range of behaviors and relate to important outcomes, such as task performance (Judge & Illies, 2002). Research has also shown individual differences more specifically affect the level of personal goals that people set (VandeWalle, Crone & Slocum, 2001) as well as the type of goals they set (Brett & VandeWalle, 1999). Two individual difference factors that seem particularly salient to the goal calibration process are trait goal orientation and trait conscientiousness.

Trait Goal Orientation. Goal orientation is an individual difference factor that relates to the focus a person places on doing a task and the goals they spontaneously set in task situations (Dweck & Leggett, 1988). There are three generally accepted types: mastery goal orientation, performance-prove goal orientation, and performance-avoid goal orientation. People with a mastery goal orientation focus their effort on mastering a task, as they believe that their abilities and competencies will grow over time (Button, Mathieu, & Zajac, 1996). Tasks are seen as a means to learn and grow. As such, individuals with a mastery goal orientation are more likely to see negative feedback as diagnostic information rather than signs of failure.

Individuals with a performance-prove or performance-avoid goal orientation both focus on task performance, but how they frame performance is very different. People with a performance-prove goal orientation, see tasks as a means to show their task ability and that they can perform at a high level (Button et al., 1996). Tasks are a means for showing others their high skill. People with a performance-prove goal orientation want to achieve high performance. Thus, achievement through high performance is their focus.

Individuals with a performance-avoid goal orientation, in contrast, are focused on avoiding demonstration of poor task ability. They doubt whether they can achieve, and thus in tasks try to avoid engaging in behaviors that might reveal their poor ability (Elliot & McGregor, 2001). For individuals high in performance-avoid goal orientation the focus is placed on avoiding task related elements that could make it appear they are performing poorly. As such, individuals with a performance avoid goal orientation are likely to see negative feedback as a sign of failure.

Goal orientation and the personal goal setting process. A number of studies have looked at the effects of trait goal orientation on the level of personal goals set in between subject designs. A meta-analysis by Payne, Youngcourt, and Beaubien (2007) summarized such work. Trait mastery goal orientation was found to have a sample weighted mean of r = .16 and trait performance- avoid goal orientation was found to have sample weighted mean of r = -.14 with personal goal level. Trait performance-prove had a non-significant effect. These results suggest the individuals high in mastery goal orientation set significantly higher personal goals while individuals high in performance-prove goal orientation set significantly lower personal goals.

Work by VandeWalle, Crone and Slocum (2001) specifically looked at how trait goal orientation affected personal goal setting after previous task performance. In a college course students were given their scores for the first class exam and norm data comparing their score to their classmates. After this feedback was given, the students were asked to set exam grade goals for the second class exam. VandeWalle et al. (2001) performed in LISREL a mediated goal orientation model for Time 2 performance, finding a significant positive path between trait mastery goal orientation and personal goal level and a significant negative path between trait performance-avoid goal orientation and personal goal level. No significant path was found for performance-prove goal orientation and personal goal level. These results suggest that after feedback trait mastery goal orientation has a positive effect on personal goal level while trait performance-avoid has a negative effect on personal goal level. These results, along with those of Payne et al. (2007), suggests that trait mastery and performance-avoid goal orientation, affect the level of personal goal set by individuals.

Trait goal orientation effects on goal calibration. While the previously mentioned relationships between trait goal orientation and personal goal level are at the between person level of analysis, they do suggest potential within person effects on the goal calibration process. Individuals with a mastery goal orientation believe they can get better at a task. As such, current goal failure is likely to have less of an impact on their belief of what they can ultimately achieve. Negative feedback is a means to diagnose what needs to be learned, rather than information that suggests current goals are unrealistic or unattainable.

This focus on the ability to improve performance on a task held by individuals with a mastery goal orientation could affect their personal goal calibration process. For individuals high in mastery goal orientation, current discrepancies are not interpreted as direct indicators of lack of ability, and this might affect how much goal revision they engage in when faced with goal-performance discrepancies. In terms of goal calibration and the Bayesian process that underlies it, mastery goal orientation could lead to stronger weight placed on the initial goal compared to actual previous performance data. People high in mastery goal orientation are likely to think that the goal is still attainable in the future, even in the face of current goal-performance discrepancies. As such, it is reasonable to think the goal calibration effect will be weaker for those high in mastery goal orientation. As such it is hypothesized that:

Hypothesis 4: The fit between goal calibration through the mechanism of Bayesian updating and personal goal revision over time will be moderated by trait mastery goal orientation such that the relationship will be weaker for individuals who are higher in trait mastery goal orientation.

For individuals high in trait performance-avoid goal orientation we might expect the opposite to happen. Individuals high in trait performance-avoid goal orientation strive to avoid showing poor ability at a task (Elliot & McGregor, 2001). As such, negative feedback offers evidence of poor ability and is something to be avoided. Goal-performance discrepancies suggest failure to performance-avoid goal orientation focused individuals and thus are undesirable. In such an environment, goal revision offers a ready means to reduce goal-performance discrepancies. Revising personal goals to likely future performance levels, thus, offers an effective means to avoid discrepancies. Goal calibration through Bayesian updating offers a strong method to make such predictions and thus might be especially salient to individuals high in performance-avoid goal orientation. As such it is predicted that:

Hypothesis 5: The fit between goal calibration through the mechanism of Bayesian updating and personal goal revision over time will be moderated by trait performance-avoid goal orientation such that the relationship will be stronger for individuals who are higher in trait performance-avoid goal orientation.

Conscientiousness. The five-factor model of personality is arguably the most thorough and well-validated theory of human personality to date, and has been applied in a wide range of research projects (Digman, 1990, Costa & McCrae, 1992). One Big Five personality trait that has been found to be especially important to performance related constructs is conscientiousness (Judge & Illies, 2002). Conscientiousness is a personality trait that encompasses the degree to which an individual is persistent, planful, organized and achievement oriented (Barrick, Mount, & Strauss, 1993). Highly conscientious individuals are known to display task persistence, attention to detail, and a desire to perform well (Hough, 1992). Conscientiousness has been found in meta-analysis to be a strong predictor of performance, r =.24 (Judge & Illies, 2002).

Conscientiousness and the personal goal setting process. One of the means through which conscientiousness leads to greater performance is by affecting individuals' personal goal level. Research by Barrick et al. (1993) found that for sales people, the higher the level of conscientiousness, the more likely an individual was to set goals and the more committed they were to a goal. Conscientious individuals were more likely to spontaneously set goals and showed greater levels of commitment to goals held.

In the meta-analysis of Judge and Illies (2002), the average effect of conscientious on personal goal level was examined. It was found that conscientiousness had a positive relationship with goal setting motivation level (a category made up primarily of studies looking at personal goal level) with the weighted mean r = .22. Individuals high in conscientiousness tended to set higher goals than individuals low in conscientiousness.

Conscientiousness effects on goal calibration. The previous empirical and theoretical work on conscientiousness gives some illumination on how the personality trait might affect the goal calibration process. Judge and Illies (2002) offer evidence that people high in conscientiousness set higher personal goals. This might suggest less sensitivity to goal-performance discrepancies. The theoretical description of conscientiousness also focuses on individuals high in conscientiousness being persistent and achievement oriented. This means they set higher goals and then persist at working towards those goals. In the model of goal calibration through the process of Bayesian updating, previous performance information is weighed in order to revise personal goals to more accurately reflect likely future performance. We might expect that people high in conscientiousness are more likely to persist at existing goals and continue to strive to achieve them. As such, we might think that goal calibration would have a weaker effect for individuals high in conscientiousness. It is predicted that:

Hypothesis 6: The fit between goal calibration through the mechanism of Bayesian updating and personal goal revision over time will be moderated by conscientiousness such that the relationship will be weaker for individuals who are higher in conscientiousness.

Methods

Procedure

To test the proposed hypotheses, 155 college students at a large Midwestern university participated in the experiment for course credit. The participants signed up for the experiment using an online subject pool system where they signed up for a particular laboratory session time. They also filled out a survey through the online system that measured their levels of trait goal orientation and trait conscientiousness through self-report. The participants then took part in a lab session approximately one half hour in length. They were seated at a computer by an experimenter and taught the basics of how to do the task used in the experiment. Participants engaged in a practice block of the task and then were asked to perform a temporary worker hiring task over 10 blocks of trials. At the end of each block, participants received feedback informing them of their exact score during that block. Participants set personal goals after the practice block for block 1 and then set a new personal goal between each block. This experimental set up was ideal for testing the hypotheses, as it provided an environment where participants got clear score performance feedback to use in a Bayesian updating process and a reasonable number of trials over which to make such estimations.

Task

The task used was a temporary worker hiring task with a 4-armed bandit design. In the task participants were given four different companies from which to hire a temporary worker for that particular workday. They were asked to make a hiring decision by clicking on one of the companies. They gained 1 point if the temporary worker was successful and 0 if the temporary worker was not. Whether a worker hiring decision was successful or not was immediately apparent, as a running score for the participant was kept on screen at all times. Each company had a different probability for success. The best strategy was to hire exclusively from the company that had the highest rate of success, which is the same across all blocks. The temporary hiring agencies had success probabilities of 20%, 40%, 60% and 80%. This task can be seen as a Multiple Cue Probability Learning (MCPL) task, with participants needing to learn choosing which of the four temporary hiring companies will lead to greater performance. Thus, while this is a simple task it does have a learning component. This type of task is consistent with tasks used in the goal setting literature such as the stock prediction MCPL task of Earley et al. (1989) and course scheduling tasks used in a number of studies (ex. Winters & Latham, 1996).

Participants made decisions in blocks of 50 decisions. The experiment consisted of 1 practice block of 20 decisions and then 10 blocks of 50 decisions. For a normal block the expected score based on using only the best agency for all decisions (average 80% success rate) was 40 points out of 50. At the beginning of each block the participants were given an assigned goal and asked to write a personal goal for the upcoming block.

There were 4 conditions in the experiment. These conditions varied in terms of what goals were given and the goal progression over time. They represent often-used goal manipulation types in the goal setting literature (Locke & Latham, 2002). The first condition was a positive goal discrepancy condition that involved goals that started at assigned goal levels of performance below those of what participants were likely to obtain, with the assigned goal increasing over time. The second condition was a negative goal discrepancy condition that started at assigned goal levels that were well above what participants were likely to obtain, with the assigned goal decreasing over time. These two conditions represented a way to examine if goal discrepancy type had an impact on how people revise their goals, as positive and negative discrepancies are potentially different environments for participants to make decisions in (Phillips et al., 1996). The third condition was an assigned "do your best' goal. The forth condition was a static specific and difficult performance goal. These two conditions represent the type of goals seen in most work that makes assigned goal comparisons (Locke & Latham, 1990). For the purposes of this dissertation, these differing assigned goals acted as different goal environments to examine how well Bayesian updating predicts actual goal revision, as well as how strong assigned goals affect personal goals. Participants were expected to engage in goal calibration in all four conditions in a similar way and, as such, no predictions based on condition were posited.

The first condition had positive goal discrepancies as participants were given increasing goals. In block 1 participants were given a goal of getting 5 points (out of a possible 50) for block 1. In each block after block 1, the point goal was increased by 5 points (i.e. 10 points for block 2, etc.), until the goal for the final block, block 10, was scoring 50 points (out of a possible

50). Thus, the condition involved assigned goals that increased over time, increasing from block to block by 5 points. This goal condition represented an assigned goal state where assigned goals were increasing over time in a task, with high initial positive goal discrepancies.

The second condition had negative goal discrepancies as the score goals started at the highest point possible and decreased over time. For block 1 the goal was to get a score of 50 points (out of a possible 50). In each block after block 1, the goal decreased by 5 points (i.e. 45 points for block 2, etc.) until the goal was 5 points (out of a possible 50) for block 10, the final block. Thus, goals started at the highest possible level of performance and decreased from block to block by 5 points. This goal condition represented an assigned goal state where assigned goals were decreasing over time in a task, with high initial negative goal discrepancies.

In the third condition participants were given a goal of “do your best” for all 10 blocks. The exact wording of the goal was “do your best to achieve a high score.” Participants in this condition were given a goal focused on getting a high score without a specific numerical performance referent. Such goals are often examined in goal type comparisons (Locke & Latham, 1990).

In the fourth condition, participants were given a static goal of a specific numerical value across all 10 blocks. The goal assigned was to get a score of 42 out of 50. This goal was assigned based on the 85th percentile of performance on the task. Such a basis is consistent with conceptualizations of a specific and difficult goal (Locke & Latham, 1990; Winters & Latham, 1996). This goal condition represented the common type of static assigned goals found in much goal setting work.

Scales

General descriptions of all scales used in this research can be found below. Full scale items used can be found in Appendices B, C, D, E, and F. All scales used have been previously used in relevant research work and/or fit with current theory of related research constructs.

Self-set goals. At the beginning of each trial block, participants were given their assigned goal for the block and then asked to write their personal goal. The exact wording of the question was "What is your personal goal for the next block?" Participants then answered this question with their personal goal. The person's assigned goal was visible on the sheet used to record the personal goal so that deviation from assigned goal would not be due to incorrect recollection of the assigned goal or such related factors.

Trait goal orientation. Trait goal orientation was measured using the 13-item scale of Vandewalle (1997) with the scale having sub-scales for mastery goal orientation (4-items), performance-approach goal orientation (4-items), and performance-avoid orientation (5-items). All items were rated on a 5 point scale from 1 ("strongly disagree") to 5 ("strongly agree.") The reliability of the mastery goal orientation scale was $\alpha = .803$. The reliability of the performance-avoid goal orientation scale was $\alpha = .814$.

Trait conscientiousness. Trait conscientiousness was measured using a 20-item scale from the International Personality Item Pool (2001). All items were rated on a 5 point scale from 1 ("strongly disagree") to 5 ("strongly agree.") The reliability of the conscientiousness scale was $\alpha = .916$.

Data Analyses

All hypotheses were tested using the SPSS statistical program. Optimal Bayesian prediction decisions were calculated based on the equations above and the actual participant data distributions using the Kalman Filter algorithm found in the R package “State Space Models in R” (“SSPIR”) in the R statistical program. The Kalman Filter algorithm is one of the most used methods of calculating optimal Bayesian updating decisions (Barker, Brown & Martin, 1995). Constant growth model predictions were calculated using the base program of the R statistical program.

The differences between goal model predictions and actual individual personal goal setting were examined by calculating root mean squared error (RMSE) between the predictions of the three models (goal calibration, constant growth, and Goal Setting Theory) and participant personal goals. These calculations were done for each participant in each trial. For hypothesis testing these RMSE per trial values were averaged across all ten trials of the experiment.

Graphs were created using the SPSS statistical program. All graphs can be found in Appendix A, Figures 1 through 8.

Results

General Analysis of Data

Table 1 presents the descriptive statistics and intercorrelations of the between subject variables. As predicted by Goal Setting Theory (Locke & Latham, 1990), personal goals and task performance had a significant positive correlation (r = .60). This also makes sense in a goal calibration perspective, as people that are performing better should also set correspondingly higher goals. Mastery goal orientation was found to have a significant negative correlation with performance-avoid goal orientation (r = -.35), a result consistent with the goal orientation meta-analysis of Payne et al. (2007). Such a negative relationship seems plausible based on the different foci each of these types of goal orientation brings to a task situation (i.e. developing new skills vs. avoiding showing poor ability).

Looking to the root mean squared error of the three goal setting models compared to personal goals at the between subject level, some interesting results are found. Both mean performance (r = .20) and mean personal goal (r = .32) correlate positively with higher levels of RMSE from the Goal Setting Theory model. This suggests that the more people differ from Goal Setting Theory predictions the higher personal goals they set and the better they perform. This makes sense when considering that some personal goals were greatly lower than average performance (mean = 33.92) and that the average assigned goal for the increasing goal and decreasing goal conditions was also below average performance (mean assigned goal = 25). Thus, for example, in block 3 participants in the increasing goal condition had an assigned goal of 15 but a mean performance level of 31.05. People setting a higher goal than performance at such a time needed to differ from the assigned goal.

Another highly significant relationship is found between RMSE for the goal calibration model and the RMSE for the constant growth model, with a positive correlation of r = .97. This means that as a person's personal goals differ from a goal calibration model they will also tend to differ from the constant growth model. This very high correlation suggests significant similarity in prediction between the two models.

The intercorrelations between variables were also calculated at the within person level. These correlations are presented in Table 2. The only significant relationship was between goal calibration model RMSE and constant growth model RMSE with an $r = .72$. Given the very strong relationship between the two variables at the between subjects level, this relationship makes a great deal of sense. If the two models are offering relatively similar predictions it would be expected they would be related at the within person level as well.

When examining the overall pattern of data, one area of significant interest is the degree to which participants actually engaged in goal revision from assigned goals. Across the conditions that involved a specified assigned goal 93.8% of participants had a goal that differed from that assigned goal at least once. Thus, almost all participants revised their personal goal from the assigned goal during the course of the experiment.

Figures 1 through 4 graph the difference between participants' assigned goals and their actual mean personal goal in each of the 4 experimental conditions. The graphs show sizable differences in participants' personal goals compared to their assigned goals. In Figure 1 we see that in the increasing goal condition participants started with personal goals well above the assigned goal of 5 points, increased that personal goal over time, and then leveled off, not following the assigned goals as it rose in the last 3 trials to 40 points and above. In Figure 2 we see that in the decreasing goal condition participants started with a personal goal below the assigned goal of 50 and keep at relatively the same personal goal level even as the assigned goal decreased over time. In Figure 3 we see that in the absence of a numerical assigned goal participants increased their goal slowly over time, ultimately leveling off in the later trials. In Figure 4 we see that for the assigned static goal of 42 points participants started with a personal goal below that level and increased the goal slowly over time, never reaching the assigned goals of 42 points. These 4 graphs illustrate that participants were not following the assigned goal closely over time and for 3 of the 4 conditions we see a relatively consistent pattern of participants slowly increasing personal goals over time and then leveling off in the later part of the experiment (the other condition, decreasing goals over time, had participants initial personal goals start at close to the goal level that the participants in the other conditions would ultimately level off at).

Table 3 illustrates these patterns in personal goals by condition through dividing the experiment into 3 periods: early (blocks 1-3), middle (blocks 4-6), and late (blocks 7-10). In the early period participants in the increasing goals condition had the lowest level of personal goals, with a mean goal of 20.87. In contrast, participants in the decreasing goal condition had a mean personal goal of 35.25, the static goal condition had a mean personal goal of 35.10, and the "do your best" goal condition had a mean personal goal of 30.18. So, in the early period we do see mean goal differences between the increasing goal condition and the other conditions. Worth noting, however is that while the mean goal of the increasing goal condition (20.87) was lower than the other conditions, the average assigned goal for the period in the increasing goal condition was 10 points. While participants in the increasing goal condition did not have personal goals as high as other conditions they were still much higher than their assigned goals.

Looking to the middle period (blocks 4-6), personal goals across all condition begin to converge. The average goal in the increasing goal condition jumped by over 8 points (from 20.87 to 28.98), participants in the "do your best" condition increased their mean personal goal from 30.18 to 34.82 and participants in the other two conditions stayed within about 1 point of their early period mean personal goals. While the average assigned goal for the decreasing goal condition fell from 45 points to 30 points, participant personal goals only decreased by 1.15 points. Participants in the decreasing goal condition were unresponsive to the changes in assigned goals.

In the late period of the experiment (blocks 7-10) the personal goals of participants across conditions converged even more. The difference in personal goals based on condition was only 2.65 points between the condition experimental group with the highest mean ("do your best" goal condition) and the lowest mean (decreasing goal condition). The mean personal goal level for the increasing goal condition jumped almost 8 points (36.87 vs. 28.98) but was well below the average assigned goal level for the period of 42.5 points. The decreasing assigned goal condition had its average assigned goal fall to 12.5 points but the average personal goal actually increased slightly from the middle period, increasing from 34.10 to 34.72. Personal goals in this period seem detached from assigned goal level and relatively similar across conditions. This makes sense from a goal calibration perspective, as participants across conditions got similar performance scores and thus would revise their personal goals toward similar personal goal levels.

The perspective that task performance had an impact on personal goals is shown clearly in the breaking of the task into early, middle, and late periods, as illustrated in Table 3. In the 4 conditions in the late period of the task the difference between performance and personal goal is no higher than a 1.78 point difference (for the increasing goal condition). Actual performance and personal goals are very close together for task participants. Figures 5 through 8 plot personal goals versus actual performance for all four conditions. As can been seen in the graphs, over time the personal goals tend to get closer to actual performance levels and generally remain around those performance levels.

Table 4 compares across all participants average performance and personal goals for all 10 trial blocks. In block 1 there is a difference of approximately 4.08 points between performance and personal goals (30.78 vs. 26.70) but for future blocks the difference is smaller, with no other block having a difference of 2 points or more and many of the middle blocks having a difference less than 1 point. This pattern of means for performance and personal goals supports at a general level the idea that participants do use performance information to inform personal goals revision, an idea central to goal calibration theory. After this general examination of the experimental data, this dissertation now turns to direct hypothesis testing.

Hypothesis Testing

Hypothesis 1 predicted that an individual's personal goal revision processes over time would better fit a goal calibration model through the mechanism of Bayesian updating than a Goal Setting Model. Hypothesis 1 was supported, as the root mean squared error average across all 10 trials was lower for the goal calibration model (RMSE= 58.71) than the Goal Setting Model (RMSE = 166.88). Thus, the goal calibration model predicted goals offered less difference from participants' actual personal goal revision than the predictions of Goal Setting Theory. See Table 5 for more information.

Hypothesis 2 predicted that an individual's personal goal revision processes over time would better fit a goal calibration model through the mechanism of Bayesian updating than a constant growth model. This hypothesis was not supported as the goal calibration model had a slightly higher root mean squared error average across all 10 trials (RMSE= 58.71) than the constant growth model (RMSE = 55.49). Thus, in opposition to the hypothesis the constant growth model predictions offered less difference from participants' actual personal goal revision than the predictions of goal calibration. See Table 5 for more information.

Hypothesis 3 predicted that assigned goals would have a more pronounced effect on personal goal levels early in a series of occurrences in doing a task rather than later in the series. This hypothesis received some support. The hypothesis was tested by dividing task trial blocks into early (blocks 1-3), middle (4-6) and late (7-10) and examining the average root mean squared error for each. The root mean squared error for the early blocks (RMSE = 149.24) was less than the root mean squared error for the late blocks (RMSE = 229.78) as predicted, but the lowest level of root mean squared error was for the middle blocks (RMSE = 75.20). Thus, personal goals set were closest to assigned goals during the middle of the experiment, trials 4 through 6. See Table 6 for more information.

Hypothesis 4 predicted the fit between goal calibration through the mechanism of Bayesian updating and personal goal revision over time would be moderated by trait mastery goal orientation such that the relationship would be weaker for individuals who were higher in trait mastery goal orientation. Hypothesis 5 predicted that the fit between goal calibration through the mechanism of Bayesian updating and personal goal revision over time would be moderated by trait performance-avoid goal orientation such that the relationship would be stronger for individuals who were higher in trait performance-avoid goal orientation. Hypothesis 6 predicted that the fit between goal calibration through the mechanism of Bayesian updating and personal goal revision over time would be moderated by conscientiousness such that the relationship would be weaker for individuals who were higher in conscientiousness. No support was found for hypotheses 4, 5 and 6. The hypotheses were each tested using a Univariate Analysis of Variance (UNIANOVA) model predicting root mean squared error for the goal calibration model and the constant growth personal goal revision model as predicted by trait mastery goal orientation, trait performance avoidance goal orientation, and conscientiousness. While the hypotheses were based only on the goal calibration model, since the constant growth model had the lowest RMSE it seemed appropriate to test its moderation as well. Hypothesis 4 was not supported, as trait mastery goal orientation did not have a significant impact on personal goal RMSE in the Bayesian Updating Model ($F = .564$, $p > .05$) or the constant growth model ($F = .598$, $p > .05$). Hypothesis 5 was not supported, as trait performance avoidance goal orientation did not have a significant impact on personal goal RMSE in the goal calibration model ($F = .009$, $p > .05$) or the constant growth model ($F = .054$, $p > .05$). Hypothesis 6 was not supported, as conscientiousness did not have a significant impact on personal goal RMSE in the goal calibration model ($F = 1.470$, $p > .05$) or the constant growth model ($F = 1.508$, $p > .05$). These results suggest that the personality traits did not have a significant impact on how much participants differed in their goal calibration model and constant growth model predicted personal goals compared to their actual personal goals. See Table 7 and Table 8 for more information.

Discussion

General Dissertation Purpose

The purpose of this dissertation was to examine how individuals set and revise personal goals over time. While a great deal of research has looked at the between subject impact of assigned goals (Locke & Latham, 1990), our understanding of within subject personal goal revision is limited. The research that has examined within person goal revision has found it to be very different than what is predicted by Goal Setting Theory, as people often revise their goals as a function of their task experiences and performance (Campion & Lord, 1983; Donovan & Williams, 2003; Vancouver et al., 2001). While such empirical work has shown that personal goal revision takes place, the literature base has been lacking in theory to explain how such revision processes unfold. We know revision takes place but not how that revision process takes place.

This dissertation argued that personal goal revision happens through goal calibration, with Bayesian updating the mechanism by which such goal revisions are made. People use performance information they have gained through the task to revise personal goals to levels that fit more closely with predicted performance. Such goal revision happens because goal-performance discrepancies are unpleasant (Carver & Scheier, 1990) and performing a task gives people a more clear idea of what their future performance should be.

Goal calibration focuses on Bayesian updating as the medium for personal goal revision due to a significant body of work that suggests that the cognitive processes of people often have a Bayesian basis, including processes such as casual inference (Steyvers et al., 2003) and symbolic reasoning (Oaksford & Chater, 2001). Humans use Bayesian processes in how they generally make estimations (Peterson & Beach, 1967) and research has shown that when people make predictions on a number of topics they do so in a way that fit with optimal Bayesian predictions (Griffiths & Tenenbaum, 2006). As such, it seemed reasonable that Bayesian updating would play a significant role in personal goal setting since such revisions involve making predictions and estimations. I will now discuss the research results and examine how they are consistent and inconsistent with the proposed hypotheses. I will then discuss implications of the results and how they contribute to the personal goal setting literature.

Summary of Results

Hypothesis 1 predicted that a goal calibration model would be a better fit for personal goal revision over time than a Goal Setting Theory Model. This hypothesis was supported, with the goal calibration model having a much smaller amount of RMSE from actual participant personal goal revision than the Goal Setting Theory Model (RMSE= 58.71 vs RMSE = 166.88). This result fits well with the existing literature base on personal goal revision. Research suggests that people often make revisions from initial or assigned goals levels over time as they engage in a task repeatedly (Campion & Lord, 1982; Donovan & Williams, 2003; Vancouver et al., 2001). Goal Setting Theory predicts people will generally follow assigned goals over time (Locke & Latham, 1990) but the results here certainly suggest revision is a common part of the personal goal process when we examine it within a person over time. These results support the idea that the natural personal goal revision process that people engage in is closer to goal calibration than Goal Setting Theory.

Hypothesis 2 predicted that a goal calibration model would be a better fit for personal goal revision over time than a constant growth model. This hypothesis was not supported, with the goal calibration model having a similar but slightly higher amount of RMSE than the constant growth model (RMSE= 58.71 vs. RMSE = 55.49). This result is surprising, as the previous work of Griffiths and Tenenbaum (2006) offers support for Bayesian updating playing a significant role in how people make estimations. This might suggest that constant growth models should be examined in more detail as having explanatory value in personal goal setting.

There is one major point that needs to be considered in potentially understanding this result and that is the differences in information base used in the goal calibration model compared to the constant growth model. For the goal calibration model the only information used was the performance data, previous variance information, and past prediction values for the goal level. This meant, for instance, when the goal calibration model predicted the goal a person would set for block 4 the model only had the data for the person's actual performance from blocks 1-3 and their a priori estimates. In contrast, the constant growth model made predictions based on all the data for a participant. So, for example, when it predicts the personal goal a person would set for trial 4 it has access to all the data before block 4 and after block 4 in making an estimation. The constant growth model had a lot more information to work with in making predictions. Taking this difference in amount of information into account it makes sense that the constant growth model would ultimately perform better.

When we consider how a person would actually go about revising personal goals, however, the goal calibration model that only looks at previous performance seems potentially more plausible as a mechanism. A participant engaging in a task in real time will not have that information about future performance or goals levels to take into account when revising personal goals that the constant growth model does. The constant growth model assumes that the person is changing the goal level at a consistent rate over time without particular regard to task related information. The constant growth model is looking at the overall trend of the personal goals the person has set over time. One might think that in a task set-up where there is more volatility in performance levels the constant growth model might perform differently. Future research needs to examine if the good fit of the constant growth model with personal goal revision is impacted greatly by task and performance related elements.

Hypothesis 3 predicted that assigned goals would have a more pronounced effect on personal goal level early in repeatedly doing a task than later in repeatedly doing a task. Mixed support was found for this hypothesis. The RMSE of assigned goals compared to actual personal goal for early blocks (blocks 1-3) in the experiment was lower than in later blocks (blocks 7-10) with a RMSE of 149.24 vs. 229.78. At the same time, though, the trials in the middle (blocks 4-6) had the lowest RMSE of assigned goals from actual personal goal setting (75.20). So while personal goals were more different from assigned goals later in the experiment they were the closest to assigned goals in the middle of the experiment. These results seem initially somewhat puzzling when compared to other within person goal revision empirical work, which tended to find participants revised their goals away from initial/assigned goals more as time passed (Campion & Lord, 1982; Donovan & Williams, 2003).

One likely potential explanation for the results arises when examining participant personal goals and the progression of assigned goals. The average personal goal for participants across all blocks was 33.75. The assigned goals for the middle blocks (blocks 4-6), in the increasing goal condition were 20, 25, and 30, while the assigned goals for the decreasing goal condition were 35, 30, and 25, respectively. This means that in the middle blocks the assigned goals were right around the goal levels participants were setting naturally. As such, it is perfectly reasonable that the personal goals and assigned goals would be closer together regardless of the degree to which participants were actually using them as a guide for behavior. RMSE measures how similar the values are, not necessarily how participants are using the assigned goals. Future research that includes different assigned goal manipulations could look at this issue more fully.

Hypotheses 4, 5, and 6 looked at potential personality characteristic mediators to the fit between goal calibration and personal goal revision. The particular factors examined were mastery goal orientation, performance-avoid goal orientation, and conscientiousness. All three hypotheses did not receive support. The factors did not have impact on the RMSE of goal calibration compared to personal goal revision. They also were found to not have an impact of the fit of the constant growth model compared to participant personal goal revision.

Trait mastery goal orientation was predicted to impact goal calibration fit due to its focus on learning a task and seeing failure, as shown in goal-performance discrepancy, as part of the learning process rather than as a reason to revise goals downward. The work of Payne, Youngcourt, and Beaubien (2007) had found that people with higher trait mastery goal orientation tended to set higher goal levels, with VandaWalle et al. (2001) finding them to also set higher goals after an initial round of feedback. It is important to note, however, such work looked at between individual effects and initial/secondary goal choice, not how a particular individual revises goals over time. It is quite possible that goal choice is impacted by trait mastery goal orientation but doesn't impact how an individual revises such goals over time and repeated task performance. Future research could look at such issues in more detail.

Research by Brett & Vandewalle (1999) on the impact of trait goal orientation on the type of goals set also offers another potential explanation. They found that people high in dispositional mastery goal orientation were more likely to set goals with content focused on learning the task rather than performance related elements. If that is the case it seems possible that people with strong mastery goal orientation may have set and revised numerical goals in a similar way to other participants but were also following learning goals that were not captured by the experiment. Thus, they revised their numerical performance goals downward but kept working toward learning goals focused on mastering the task and learning new skills. Such an issue could be examined using a multiple goal perspective in future work.

Trait performance-avoid goal orientation was expected to impact goal calibration fit because individuals high in performance-avoid goal orientation are particularly focused on avoiding showing failure and thus, setting goals that were close to likely performance levels would be especially appealing to them. Payne and colleagues (2007) had found that people with higher trait performance-avoid goal orientation tended to set lower goal levels, with VandaWalle et al. (2001) finding them to also set lower goals after an initial round of feedback. A similar argument as the one presented for mastery goal orientation seems plausible here. Vandewalle and colleagues (2001) did not look at how performance-avoid goal orientation impacted goal revision over time rather only one instance of goal choice after a single feedback occurrence and it seems quite possible a repeated goal revision process over time might be different in nature. It also seems possible that if Bayesian Theory is a primary way by which people make estimations (as strongly suggested by the results of Griffiths and Tenenbaum (2006)), that such estimations are done relatively automatically and thus a personality trait like performance-avoid goal orientation does not impact the process.

Conscientiousness was predicted to impact goal calibration fit because people high in conscientiousness tend to be persistent and have a desire to perform well (Hough, 1992), which would suggest they might be more likely to keep working toward a goal rather than revising it downward. Research by Barrick et al. (1993) found people high in conscientiousness tended to have higher goal commitment and meta-analytic work by Judge and Illies (2002) found conscientiousness related to higher personal goal levels. While both of these findings offered a hint as to how conscientiousness could affect personal goal revision they both came from between individual designs examining personal goals. As such, they did not offer direct information on how an individual might revise goals over time. The results here suggest that those effects may not hold at the within person level. Initial goal choice may be impacted by conscientiousness but later goal revisions may not. Persistence also suggests effort allocation, something not directly examined in this research. It is possible highly conscientious individuals revised their goals downward but still put in higher levels of effort than other people. If that was the case, the impact of conscientiousness might instead be less sensitivity to change in goal level affecting effort allocation. Conscientious people might be more willing to put in higher effort regardless of goal level or changes in goal level. Future research should examine how exactly conscientiousness impacts effort allocation and task-related perceptions.

Limitations

While this dissertation offers some potentially valuable results, there exist some clear limitations to the study. One potential limitation is the lab study nature of the experiment. While it seems probable that using goal calibration through Bayesian updating is an estimation method that people use naturally across situations (as suggested by Griffiths and Tenenbaum (2006)), the possibility does exist that goal revision might be different in a field setting where goal revision has significant work/career implications. The consequences for goal revision in a lab task are usually lower than the consequences in a work-place setting, where job status or compensation might be impacted by such decisions. Assigned goals might also be more robust in a setting where the goals are supervisor imposed and consequently more salient. Follow up research to this work could examine lab versus field differences in the goal revision process and how well goal calibration predicts goal revision in the actual workplace.

Another potential limitation of the study is that the sample here was made up entirely of undergraduate students. Undergraduate students can differ from the general population in their behaviors, attitudes, and work experiences, impacting the ability to apply research results to the general working population. Since this research was trying to look at a basic cognitive process that would apply across situations, concerns for generalizability to a work setting are not as acute as other types of research in the research base. This research examined the general goal revision process over time rather than a factor directly related to work behaviors or attitudes. Still, future work could look at how goal calibration fits goal revision processes for people that vary more in age and work experiences.

One more potential limitation of this research is the task itself. While the task fit well with the hypotheses being tested, other task environments might moderate the goal setting effect. Based on the standards of Wood (1986), the task presented here would be considered a task low in task complexity. Research in goal setting has found that task complexity can impact goal related constructs, most notably that the positive impact of specific and difficult performance goals on task performance is lessened in high complexity tasks (Wood et al., 1987). While this dissertation would predict that goal calibration unfolds the same across different task complexities, such an issue would have to be tested empirically to be certain. Tasks that are complex or confusing might make it harder for people to predict future performance, although making Bayesian updating decisions should still function in a similar manner for estimation.

Theoretical Implications and Future Research Directions

The results of this study fit with existing trends in the personal goal literature and offer significant avenues for future research in the area. Consistent with the research looking at goal setting over time (Campion & Lord, 1983; Donovan & Williams, 2003; Vancouver et al., 2001), this research found that people revised their goals significantly over time. Individuals do not keep static assigned or initial goals over time as is suggested by Goal Setting Theory, rather individuals revise their goals. Individuals are sensitive to goal discrepancies and the greater these discrepancies are, the more likely they are to revise their personal goals to reduce such discrepancies (Donovan & Williams, 2003).

While this dissertation does show this tendency of individuals to revise personal goals in response to discrepancies, it takes the research area a step further by offering a theoretical mechanism by which such revision takes place. While it was known such personal goal revision existed, the research interest area did not have clear theory on how such revisions took place over time. This dissertation proposed the revision process happens by goal calibration through Bayesian updating, as people use performance information to make estimations of future task performance in the form of personal goals. Bayesian theory seems to be inherent in how people make estimations (Griffiths & Tenenbaum, 2006; Peterson & Beach, 1967) and thus seems like a probable mechanism.

This dissertation found that goal calibration did indeed offer a better fit with individuals' personal goal revision processes than Goal Setting Theory. This suggests that goal calibration is a better model for explaining personal goal processes than Goal Setting Theory. Unexpectedly, a constant growth model was found to be a slightly better fit with participant personal goal revision than the goal calibration model. As discussed previously, this might be due to the fact that the constant growth model has a larger information base to make goal estimations than goal calibration. Regardless, this result suggests that constant growth models should gain greater research attention in the personal goal revision literature as the results here suggest it has explanatory value.

Future work certainly needs to be done looking at the goal calibration model as well, both on its own and in competition with the constant growth model to determine the better fitting model. Both seem to help to explain personal goal revisions processes and it is possible that elements of each are used in within person goal revision. Perhaps this means that while there is a general trend of goal calibration through the mechanism of Bayesian updating that is partially driving goal revision, there is also an element unique to individuals that impacts that process that is shown through a constant growth model. It seems plausible that some of that unique individual element might be driven by individual difference factors, although the three personality characteristics examined in this dissertation did not have significant impact. Future research should examine other individual difference factors that might have an impact, such as general intelligence, positive affectivity, negative affectivity, and more directly relevant conscientiousness facets.

The results of this dissertation also suggested that individuals tend to follow assigned goals more strongly earlier in a task than later, as assigned goals had a better fit with personal goals in the early blocks of the experiment (Blocks 1-3) than in the late blocks (Blocks 7-10). This fit with the results of Donovan and Williams (2003), which found that initial track goals were more likely to be changed later in the track season. Not predicted, however, was that the best fit of assigned goals with personal goals was in the middle blocks (Blocks 4-6). As previously discussed, this effect might be just due to the changing goals in the assigned goal conditions being closest to overall average participant personal goals during those blocks. Future research could examine this more thoroughly with different changing goal conditions to see if it is indeed due to the effect described or if it does have something to do with how people use assigned goals over time.

A number of future avenues exist to build on the results found in this dissertation and address previously discussed limitations. Examination of how well a goal calibration model and a constant growth model fit personal goal revision in a field setting would be valuable. This would help build understanding of how much goal importance and potentially task familiarity impacts the goal revision process. This also would offer potential moderators of the relationship such as assigned goal salience, task type, and individual age/experience.

Another interesting avenue would be to examine whether multiple goal revision proceeds in a manner consistent with goal calibration. Multiple goal work has examined a number of factors such as incentives and discrepancies on how they impact multiple goal prioritization and effort allocation (Schmidt & DeShon, 2007; Schmidt & Dollis, 2008; Schmidt, Dolis & Tolli, 2008). Goal calibration could offer valuable information on how goal revision proceeds in such situations and what goals levels individuals set when they make such revisions.

Practical Implications

The results of this dissertation suggest some potential implications for how goals are used within organizational settings. One major implication is that if managers give work goals to their employees they cannot expect that those employees will follow those assigned goals to the letter over time. Systems like Management by Objectives (Drucker, 1976; Rodgers & Hunter, 1991) and the ProMES system (Pritchard 1990) have an inherent assumption that workers will be committed to assigned goals and make those assigned goals their personal goals over time. This study shows that a significant amount of revision happens from assigned goals over time. In fact, individuals will not necessarily even set their personal goals to the assigned goal at the beginning of a task. This is shown clearly in the increasing goal condition, where participants set trial 1 goals well above the assigned goal of five points that they were given. Managers need to be aware that employees can, and will, revise personal goals over time, with such revisions informed by actual performance information. Such revisions will affect the impact of the assigned goals on work-related performance.

A related implication is that workers will use previous performance information in determining what personal goal they set and how closely they follow an assigned goal. Previous performance is used in determining future goals. While in this study a participant had at most nine previous task performance experiences to inform them when setting a personal goal, in a work setting an employee might have years of experience doing a task over thousands (or more) performance instances. In such circumstances a worker will usually have a very clear idea of what level of performance they are likely to reach and that will inform what type of personal goal they set. Managers that think a newly assigned goal in a task with such great previous experience will be completely accepted and adopted as a personal goal will likely be sorely disappointed.

For the assigned goal to be weighed more heavily than previous performance the task, perhaps, must be seen as very different from before, with previous information seen as less relevant. In this case, a manager could frame the task differently or make changes to how performance is defined so that the assigned goal is used as a basis for personal goals rather than the worker's previous performance. This is probably a temporary solution however, as this research shows people quickly start to adjust personal goals to actual performance levels.

Managers might also consider using incentives to make the assigned goal salient. Research looking at multiple goals across different tasks has generally found that people put greater priority toward the task with the goal tied to an incentive (Schmidt & DeShon, 2007). If reaching the assigned goal leads to a valuable incentive workers will me more likely to work toward that goal.

A final practical implication of these results is the need to think about goals in the workplace as taking place in a dynamic setting. Goal setting research has traditionally looked at tasks as inherently static, with the same assigned goal given over time and workers following that assigned goal as a personal goal over time. This is simply not the case in real organizations where task elements and worker cognitions are often changing. As shown here, personal goals change over time with performance information used to make such decisions. Each performance instance of a task can be different based on the context of previous performance and current worker cognitions. Work is done in a dynamic context and organizations need to understand that fact and build it into how they assign goals and how they expect workers to use those goals over time. This research is a small step in better explicating that complexity.

Conclusion

This dissertation set out to examine how individuals revise their personal goals over time. It was predicted that people revise their goals in a manner consistent with Bayesian updating, conceptualized here as goal calibration. Support was found for goal calibration offering a better fit with participant goal revision processes than Goal Setting Theory, although a constant growth model was found to have the best fit with participant goal revision. Assigned goals were found to have a better fit with personal goals early in a series of task occurrences rather than late in a series of task occurrences, although the best fit was found between assigned goals and actual goals was in the middle of the series of the task occurrences. These results help to build our understanding of how people revise their personal goals over time and future research can help to clarify some of the ambiguous elements of the results found here. We live in a world where individuals make and revise goals often over repeated occurrences of the same and similar behaviors and tasks. As such it is vital to understand such processes central to how people engage with the world. This dissertation hopes to be a step in increasing such understanding.

APPENDICES

APPENDIX A

Tables

Table 1

Means, Standard Deviations and Intercorrelations for Between Subject Variables

				1	2	3	4	5	6	7
		Mean	**SD**							
1	Mean Performance	33.92	3.73	(-)						
2	Mean Personal Goal	33.75	5.85	**0.60**	(-)					
3	Mastery Goal Orientation	3.89	0.52	0.03	0.06	(0.80)				
4	Performance-Avoid Goal Orientation	2.93	0.75	-0.05	-0.09	**-0.35**	(0.81)			
5	Conscientiousness	3.54	0.54	0.04	0.07	**0.32**	-0.11	(0.92)		
6	Bayesian Updating RMSE	58.71	58.34	-0.03	-0.08	-0.04	0.01	0.08	(-)	
7	Constant Growth RMSE	55.49	60.24	-0.05	**-0.16**	-0.04	0.04	0.09	**0.97**	(-)
8	Goal Setting RMSE	166.68	199.30	**0.20**	**0.32**	-0.01	0.03	0.01	-0.02	-0.05

All bolded correlations are significant at $p < .05$ level. Values on diagonal are scale reliabilities if applicable.

Table 2

Intercorrelations for Within Subject Variables

		1	2	3	4	5
1	Performance					
2	Personal Goal	0.15				
3	Bayesian Updating RMSE	-0.27	-0.15			
4	Constant Growth RMSE	-0.19	-0.20	**0.72**		
5	Goal Setting RMSE	0.02	-0.29	-0.01	0.04	

All bolded correlations are significant at $p < .05$ level.

Table 3

Mean Personal Goal and Performance Over Time by Condition

Temporal Period	Variable of Interest	Overall (across conditions)	Increasing Goal	Decreasing Goal	Do Your Best Goal	Specific Difficult Goal
Early	(Blocks 1-3)					
	Personal goal	30.05	20.87	35.25	30.18	35.10
	Performance	31.65	30.15	32.00	32.04	32.56
	Average Assigned Goal	N/A	10 (5, 10, 15)	45 (50, 45, 40)	N/A	42
Middle	(Blocks 4-6)					
	Personal goal	33.32	28.98	34.10	34.82	36.00
	Performance	33.79	32.22	34.52	34.63	34.09
	Average Assigned Goal	N/A	25 (20, 25, 30)	30 (35, 30, 25)	N/A	42
Late	(Blocks 7-10)					
	Personal goal	36.56	36.87	34.72	37.37	37.28
	Performance	35.72	35.09	35.74	36.21	35.95
	Average Assigned Goal	N/A	42.5 (35, 40, 45, 50)	12.5 (20, 15, 10, 5)	N/A	42

Table 4

Mean Performance Score and Personal Goal Across Each Block

	Block 1	Block 2	Block 3	Block 4	Block 5	Block 6	Block 7	Block 8	Block 9	Block 10
Mean Performance	30.78	31.87	32.30	33.28	33.85	34.24	35.38	35.85	35.99	35.65
Mean Personal Goal	26.70	30.16	32.38	32.10	33.67	34.36	35.34	36.19	37.38	37.62

Table 5

Root Mean Squared Error Between Personal Goal Setting and Goal Setting Models

		RMSE Goal Calibration	RMSE Constant Growth	RMSE Goal Setting Theory
N	Valid	147	147	118
	Missing	9	9	38
Mean		58.71	55.49	166.88
Median		36.50	32.98	107.22
Standard Deviation		58.34	60.24	192.30

Table 6

Root Mean Squared Error Between Personal Goal Setting and Assigned Goals

		RMSE Assigned Goals Early (Blocks 1-3)	RMSE Assigned Goals Middle (Blocks 4-6)	RMSE Assigned Goals Late (Blocks 7-10)
N	Valid	114	115	116
	Missing	42	41	40
Mean		149.24	75.20	229.78
Median		112.50	41.67	53.00
Std. Deviation		159.13	105.08	336.84

Table 7

Univariate Analysis of Variance: Impact of Mastery Goal Orientation, Performance-avoid Goal Orientation, and Conscientiousness on RMSE of the Goal Calibration Model Predicting Goal Setting

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	5911.217	3	1970.406	.564	.640
Intercept	3181.248	1	3181.248	.911	.342
Mastery Goal Orientation	2288.345	1	2288.345	.655	.420
Performance-Avoid Goal Orientation	32.205	1	32.205	.009	.924
Conscientiousness	5135.522	1	5135.522	1.470	.227
Error	485492.198	139	3492.750		
Total	984291.606	143			
Corrected Total	491403.415	142			

Table 8

Univariate Analysis of Variance: Impact of Mastery Goal Orientation, Performance-avoid Goal Orientation, and Conscientiousness on RMSE of the Constant Growth Model Predicting Goal Setting

Source	Type III Sum of Squares	df	Mean Square	F	Sig.
Corrected Model	6668.495	3	2222.832	.598	.617
Intercept	1634.669	1	1634.669	.440	.508
Mastery Goal Orientation	1910.504	1	1910.504	.514	.475
Performance-Avoid Goal Orientation	199.166	1	199.166	.054	.817
Conscientiousness	5604.603	1	5604.603	1.508	.221
Error	516470.635	139	3715.616		
Total	964279.528	143			
Corrected Total	523139.130	142			

APPENDIX B

Figures

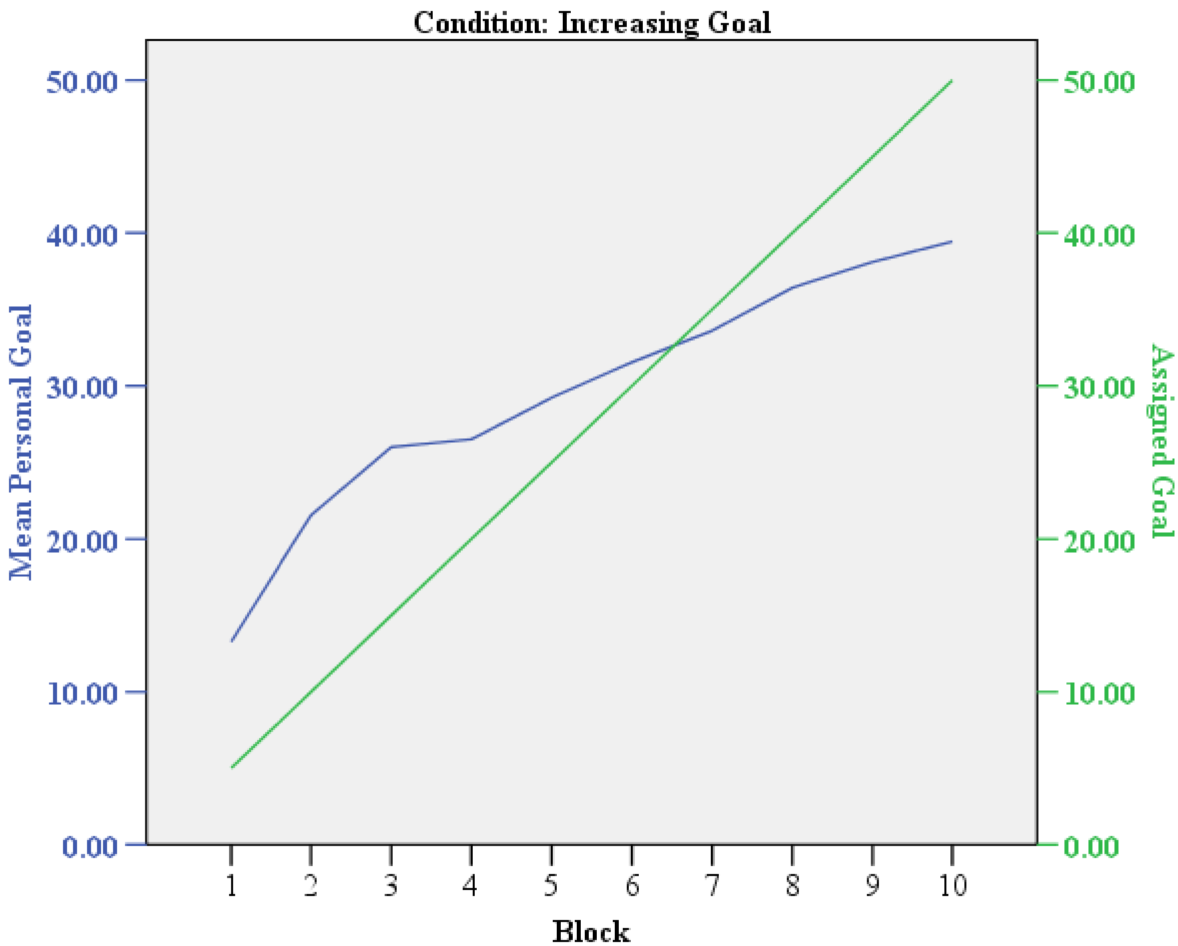

Figure 1. Increasing goal condition: Personal goal and assigned goal over time. For interpretation of the references to color in this and all other figures, the reader is referred to the electronic version of this dissertation.

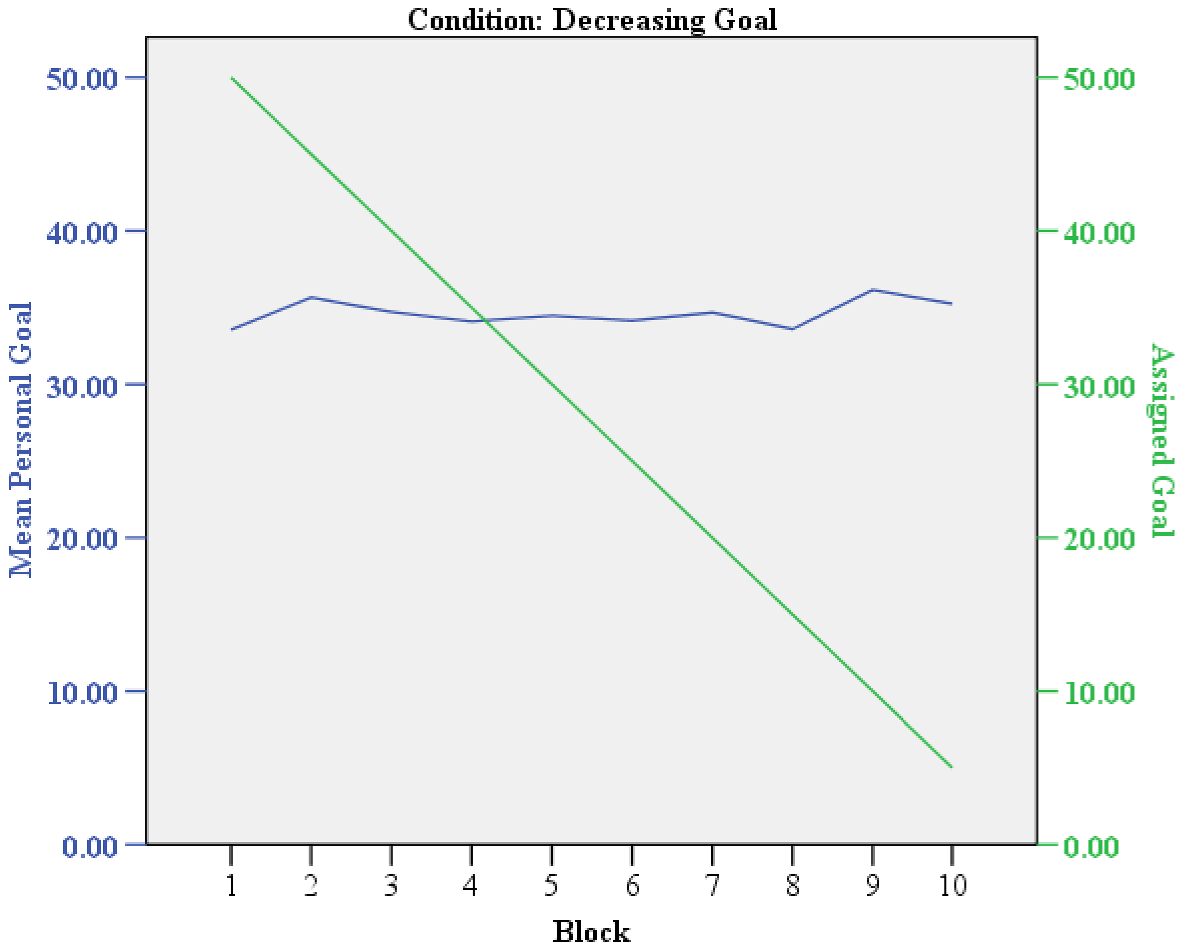

Figure 2. Decreasing goal condition: personal goal and assigned goal over time

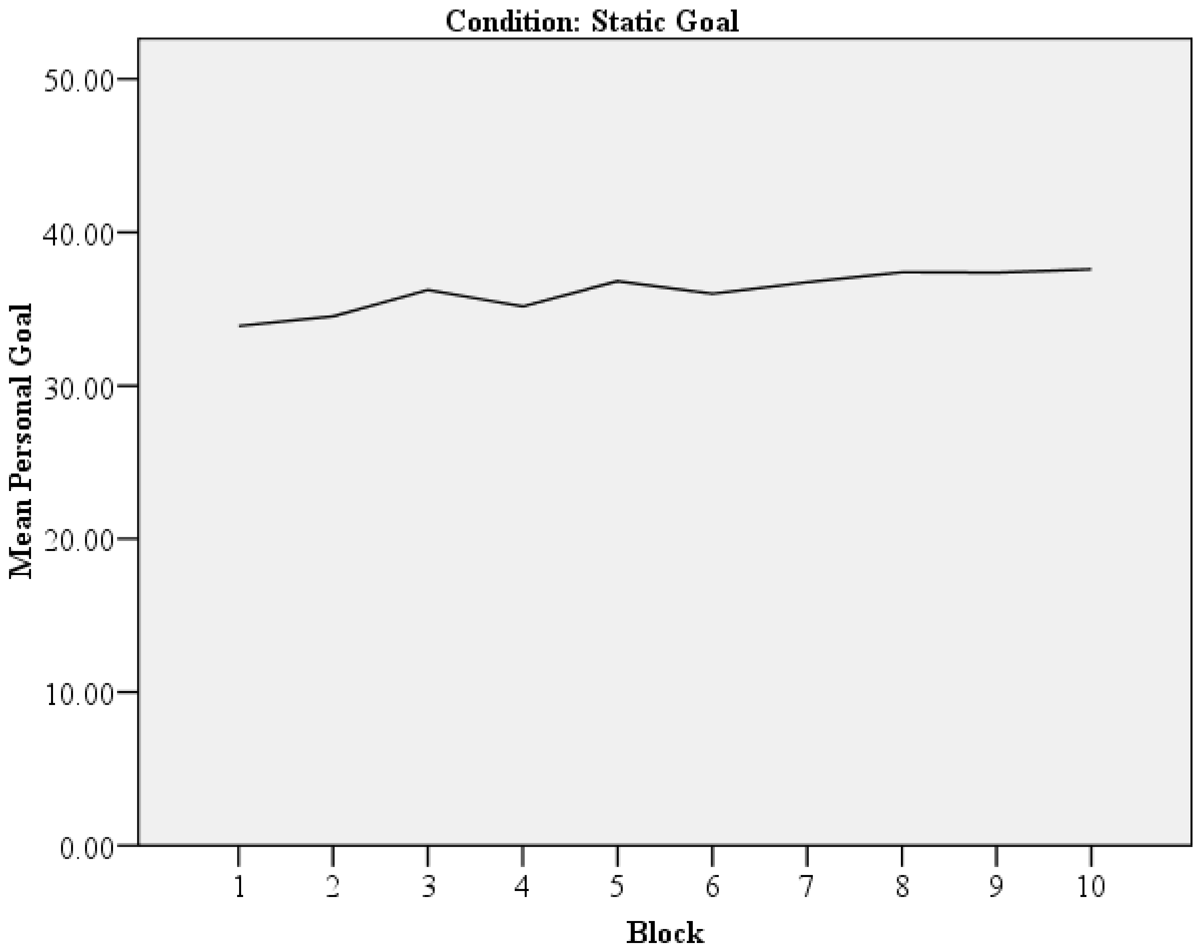

Figure 3. Do your best condition: personal goal over time

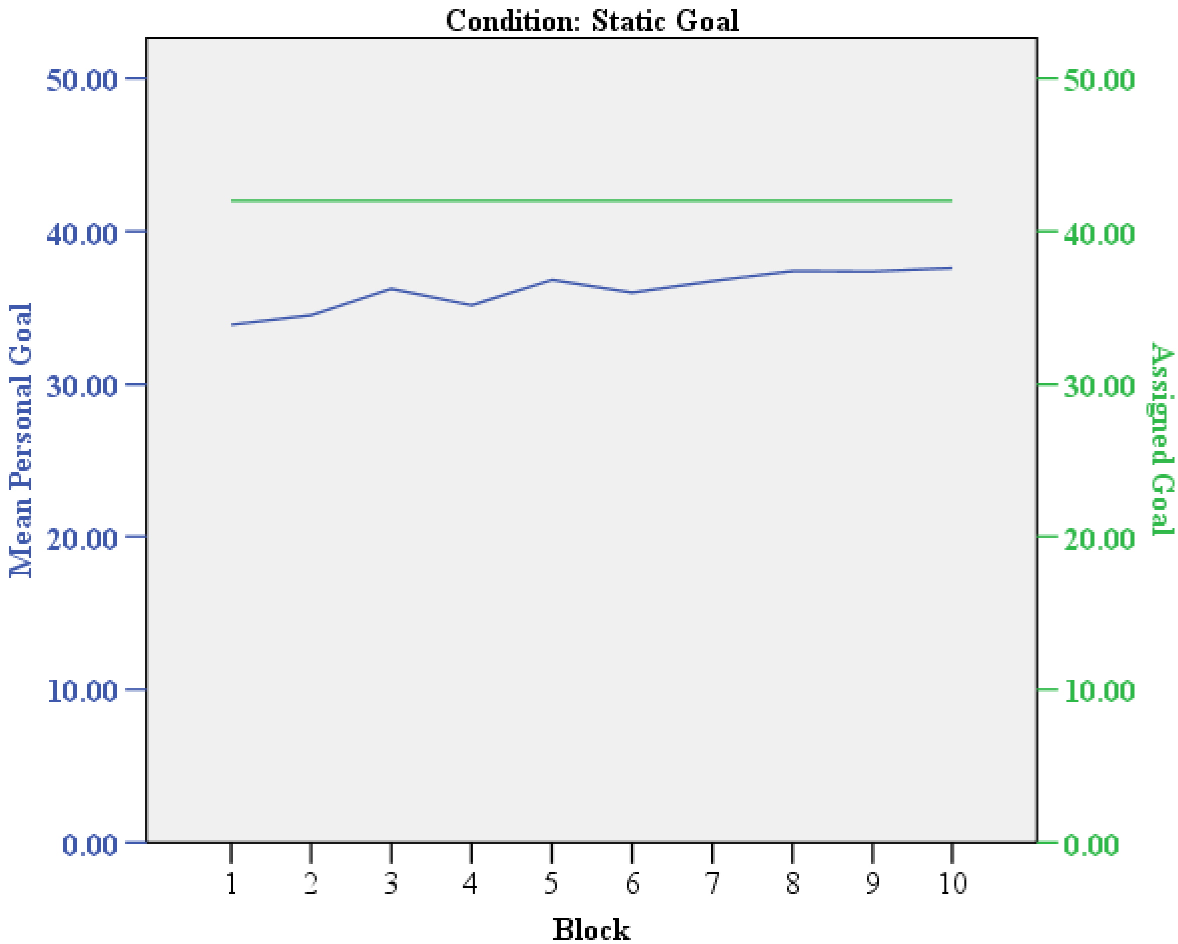

Figure 4. Static goal condition: personal goal and assigned goal over time

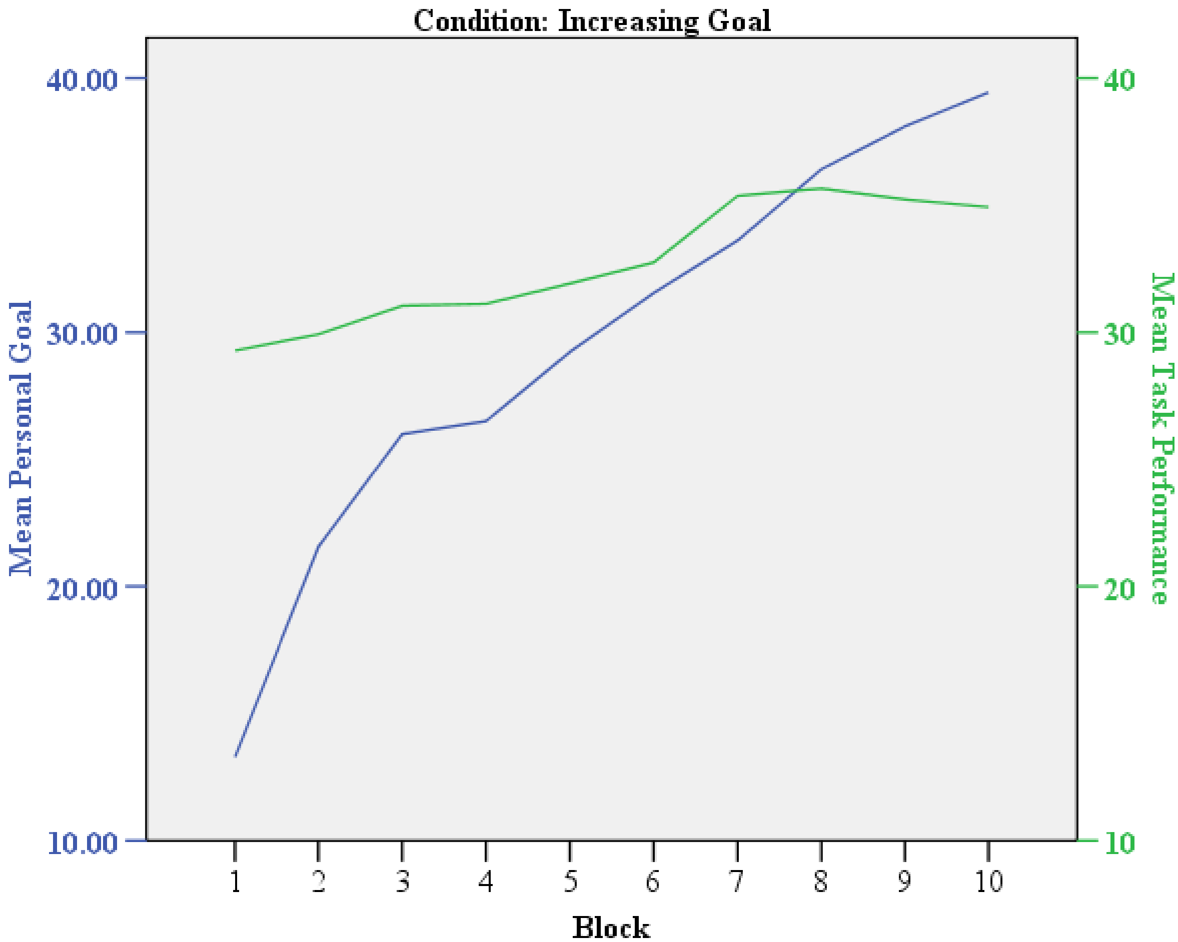

Figure 5. Increasing goal condition: personal goal and task performance over time

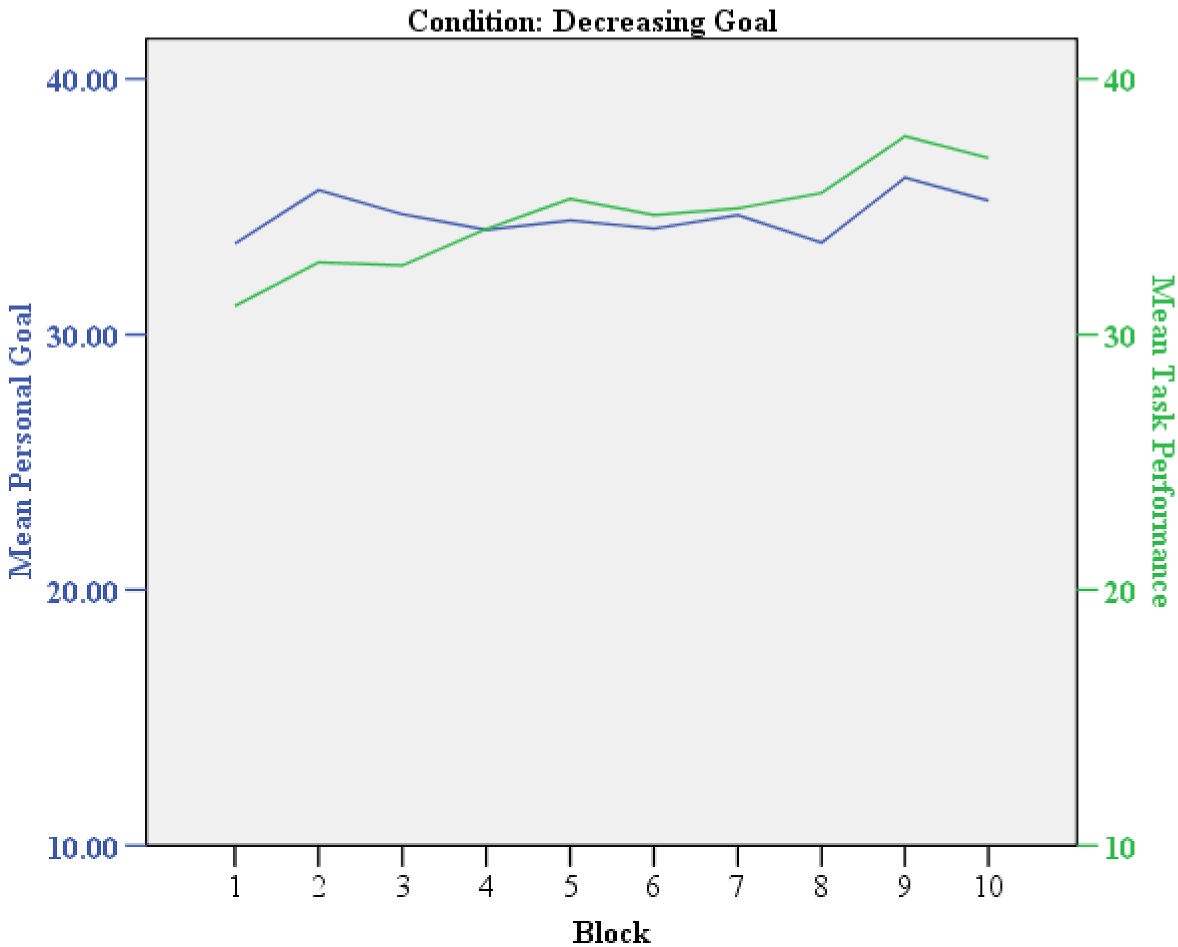

Figure 6. Decreasing goal condition: personal goal and task performance over time

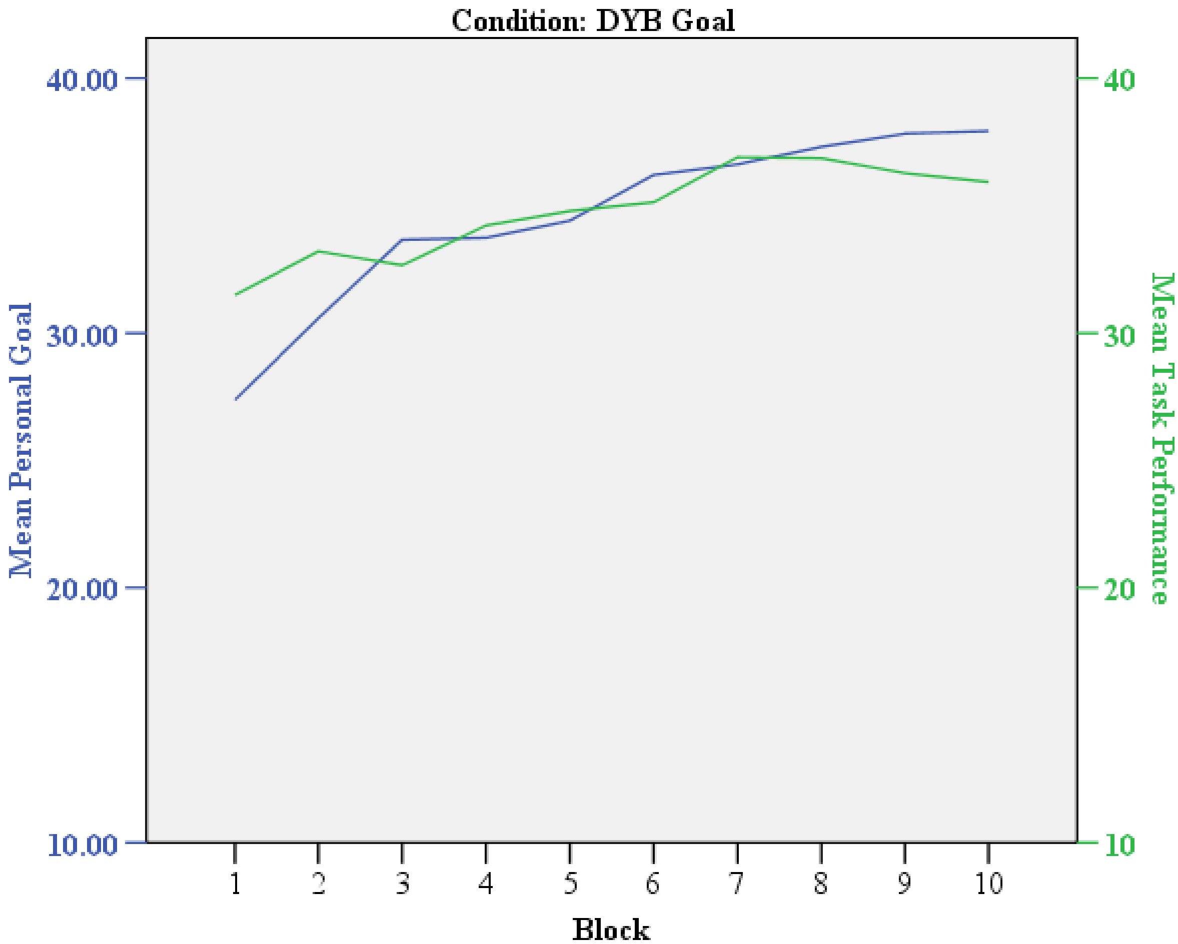

Figure 7. Do your best goal condition: Personal goal and task performance over time

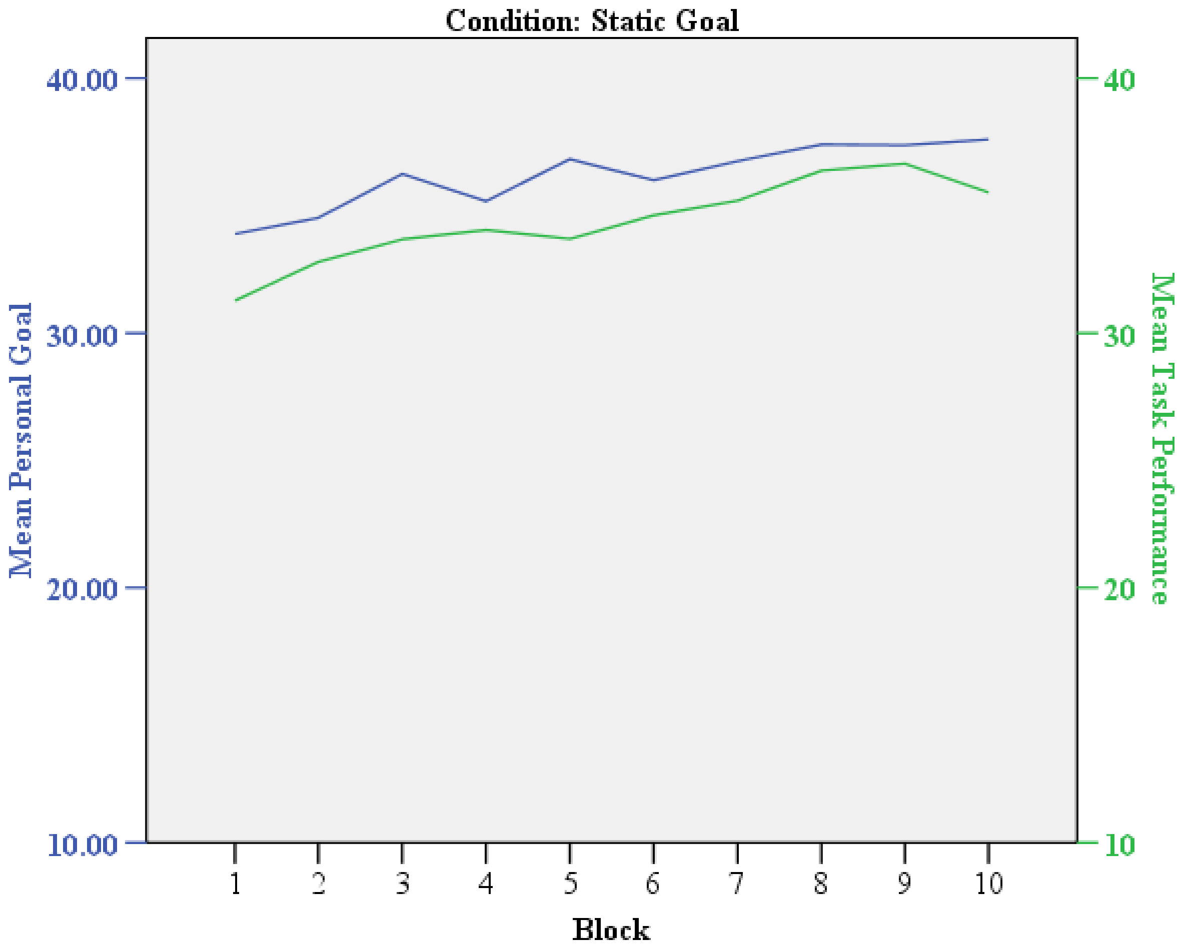

Figure 8. Static goal condition: Personal goal and task performance over time

APPENDIX C

Informed Consent Form

Electronic Informed Consent: Gameplaying

Project Title: Gameplaying

Investigators' Names: Dr. Rick DeShon and Gordon B. Schmidt

Description and Explanation of Procedure:
This study is about how people go about playing games. You will be asked in the lab session to play a game task under changing conditions. You will also be asked to answer questionnaires to help us understand your characteristics and how you interact with the game task.

If you agree to participate, you will next fill out a set of questionnaires online and then participate in a lab session doing a game task at the time you selected. Filling out the online questionnaires will begin immediately upon entering the requested information below and will take approximately 30 minutes to complete [1 credit]. It includes questions about your demographic information, your SAT/ACT scores, and other characteristics related to the game task you will learn. You will then go to the **X** lab in room **XXX** Psychology Building at your scheduled time to participate in the game task simulation which will take 1 hour (**?**) to complete [2 credits]. You will receive basic training on the game and will then practice and perform the simulation over a number of trials under different conditions. You will be asked questions about your reactions to the task during practice.

Those not interested in this research can seek other alternatives and research studies for subject pool credit by consulting their instructor or the Department of Psychology subject pool web site.

Estimated time required:
- 30 minutes for the online questions [1 Psychology subject pool credit];
- 1 hour for the lab based game task [2 Psychology subject pool credits]

Risks and discomforts:
None anticipated

Benefits:
You will gain experience completing several standard psychological measures on-line. You will also learn some task skills in the game you play in the lab. Finally, you will learn about the process of conducting psychological research.

Please DO NOT use the "Back" or "Forward" features of your browser! Use only the links to go to and from pages within this study. DO NOT open up other web sites from within this browser window!

Agreement to Participate
Participation in this study is completely voluntary. You also give permission to the experimenters to access or verify your ACT/SAT score from the University Registrar. You have been fully informed of the above-described procedure with its possible benefits and risks. You are free to withdraw this consent and discontinue participation in this project at any time without penalty. If you choose to withdraw from the study prior to its completion, you will receive credit for the time you have spent in the study (1 credit per 30 minutes).

The investigators will be available to answer any questions you may have. If, at any time, you feel your questions have not been adequately answered or you want to discuss the research, please contact the investigators (Gordon Schmidt, schmi306@msu.edu, 353-9166; Dr. Rick Deshon, deshon@msu.edu , 353-4624) or the Head of the Department of Psychology (Neal Schmitt, 353-9563). If you have questions or concerns regarding your rights as a study participant, or are dissatisfied at any time with any aspect of this study, you may contact—anonymously, if you wish— Peter Vasilenko, Ph.D., Director of Human Research Protections, (517)355-2180, fax (517)432-4503, e-mail irb@msu.edu, mail 202 Olds Hall, Michigan State University, East Lansing, MI 48824-1047
If you agree to participate, please enter the information requested at the bottom of this form. The reason you are asked for your name and PID is to ensure that you receive credit for participating in the study. Participants' identity data will be kept secure and confidential. Your identity will not be associated with your responses for any data analyses. Your privacy will be protected to the maximum extent allowable by law.
Do you fully consent to participate in the study described above?

Yes No

If you marked "Yes," please enter your PID number (do **NOT** enter the A in the box to the right): **A**

Please enter your MSU login ID (your email address **without** the @msu.edu):

Please enter your your **LAST** name (so we can give you credit for participating in the experiment):

If you marked "No," please click here to ***EXIT the experiment*** at this time.

APPENDIX D

Trait Goal Orientation Scale

(VandeWalle, 1997)

This set of questions asks you to describe your ***general*** orientation towards work. Please answer as honestly and accurately as you can.

Response scale: 1-5 (Strongly agree-Strongly disagree)

1]. I am willing to select a challenging assignment that I can learn a lot from.
2]. I often look for opportunities to develop new skills and knowledge.
3]. I enjoy challenging and difficult tasks where I'll learn new skills.
4]. For me, development of my ability is important enough to take risks.
5]. I prefer situations that require a high level of ability and talent.
6]. I'm concerned with showing that I can perform better than others.
7]. I try to figure out what it takes to prove my ability to others.
8]. I enjoy it when others are aware of how well I am doing.
9]. I prefer projects where I can prove my ability to others.
10]. I would avoid taking on a new task if there were a chance that I would appear rather incompetent to others.
11]. Avoiding a show of low ability is more important to me than learning a new skill.
12]. I'm concerned about taking on a task at work if my performance would reveal that I had low ability.
13]. I prefer to avoid situations where I might perform poorly.

APPENDIX E

Conscientiousness Scale

International Personality Item Pool. (2001). A Scientific Collaboratory for the Development of Advanced Measures of Personality Traits and Other Individual Differences (http://ipip.ori.org/). Internet Web Site.

Response scale: 1-5 (Strongly agree-Strongly disagree)

+ keyed

Am always prepared.
Pay attention to details.
Get chores done right away.
Like order.
Follow a schedule.
Am exacting in my work.
Do things according to a plan.
Continue until everything is perfect.
Make plans and stick to them.
Love order and regularity.
Like to tidy up.

– keyed

Leave my belongings around.
Make a mess of things.
Often forget to put things back in their proper place.
Shirk my duties.
Neglect my duties.
Waste my time.
Do things in a half-way manner.
Find it difficult to get down to work.
Leave a mess in my room.

APPENDIX F

Example Trial Handout

This set of questions asks how you feel about the task. Please use the scale shown below to make your ratings.

1	2	3	4	5
Strongly Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Strongly Agree

1) I am satisfied with my performance on the prior block of trials. ① ② ③ ④ ⑤
2) I met my performance goal on the prior block of trials. ① ② ③ ④ ⑤

Your Goal for the next block is:

Get a score of 5 out of a possible 50 points

What is your personal goal for the next trial? Please write it below.

These questions ask how you feel about your goal. Please rate on the following scale:

1	2	3	4	5
Strongly Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Strongly Agree

3) I intend to put forth a great deal of effort to meet my goal. ① ② ③ ④ ⑤
4) I am strongly committed to pursing my goal. ① ② ③ ④ ⑤

The table below asks you to rate how confident you are at reaching a particular score during the next block of 50 trials. Please rate your confidence in reaching that goal using the following percentages from 0% to 100% by putting an X in the appropriate box.

Percentage (%) you are confident you can reach that score

Score	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
5											
10											
15											
20											
25											
30											
35											
40											
45											
50											

APPENDIX G

Demographics Scales

This section asks for background information. Your answers are strictly for research and will not be used for any other purposes.
1]. Year in school
- Freshman
- Sophomore
- Junior
- Senior
- Other

2]. Age

3]. Gender
- Male
- Female

4]. Race
- African-American
- Asian
- Hispanic/Latino
- White
- Other

5]. Cumulative Grade Point Average (GPA)

6]. Please enter your ACT or SAT total test score. If you took both exams, please enter your score on the ACT exam. If you did not take either exam, or don't remember your score, please put 0:

7]. Major
- Psychology
- Non-Psychology

8]. Rate your experience with personal computers
- None
- Some
- A lot

9]. Approximately how often do you use a personal computer?
- Monthly
- Weekly
- Daily

10]. Approximately how often do you play video games?
- Monthly
- Weekly
- Daily

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