Continuous Learning: Choosing and Allocating Resources to Strengths and Weaknesses

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Abstract

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Continuous Learning: Choosing and Allocating Resources to Strengths and Weaknesses

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Individuals are continuously learning and improving over a lifetime. This continuous, self-directed learning can be very important for individual career success because organizations improve through the continuous learning of the employees. Yet, there is little research about how individuals choose between multiple domains. This study investigates how individuals use beliefs about their relative strengths and weaknesses to allocate resources to learning. To develop a set of hypotheses, the literatures on self-regulation, motivation, learning, and goal orientation are reviewed. Specifically, the role flexibility context of individuals, meaning how much control individuals have over which roles relevant to a particular task are most important, was hypothesized as an important predictor of learning choice. Anticipated relative improvement, or the belief in which area may improve more in a certain amount of time, was also hypothesized as a predictor and hypothesized to interact with learning goal orientation. Participants (N = 171) were assigned to either a high role flexible or a low role flexible condition and were given the chance to choose to study either a relative strength or a relative weakness. Logistic regression analyses were conducted. Role flexibility condition was a significant predictor. Anticipated relative improvement also predicted study topic choice. The predicted interaction between relative improvement and goal orientation did not relate to study topic choice. Limitations and future research are discussed in terms of construct, internal, and external validity.
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**Introduction**

Individuals are highly involved in their own education and learning at work (London, 2011; Long, 1988; 1989). For instance, within organizational settings, employees have much control over the training they obtain (Frese, Garst, & Fay, 2007), the knowledge they acquire (Grant, Fried, & Jullierat, 2011; Wang & Netemeyer, 2002), and the skills they develop (Crant, 2000; Goldstein & Ford, 2002; Grant & Ashford, 2008). Indeed, individuals spend almost half of all self-directed learning hours on job and career-related projects (Clardy, 2000; Rymell & Newsom, 1981). In university settings, faculty members spend 10% to 25% of their time keeping current in their respective fields (Brown & Hanger, 1975). Self-directed learning means that the learner freely chooses what, and in what manner, to learn (Knowles, 1975; Long, 1989). This type of learning is something that potentially occurs not only on a daily basis, but also spans across a career (London, 2011; London & Moore, 1999; Merriam, 2001), given that learning is a process that develops over time (DeRue et al., 2012). Moreover, organizations have endorsed this continuous learning as part of one’s day-to-day job because self-directed learning can play a large role in an organization’s competitiveness and effectiveness (Brown & Sitzmann, 2011; DeRue, Ashford, & Myers, 2012; Frese, Fay, Hilburger, Leng, & Tag, 1997; Goldstein & Ford, 2002; Parker, Wall, & Jackson, 1997; Sonnentag, 2003). Yet, as reviewers note (Clardy, 2000), the field knows relatively little concerning how individuals go about choosing what to learn.

For example, consider two freshmen academics. One receives top ratings on research but only mediocre ratings for teaching. The other receives top ratings in teaching but only mediocre ratings in research. The two have an opportunity to take a class on
teaching (i.e., on implementing a new and popular classroom technology) or a class on research (i.e., on using a new and upcoming statistical procedure), but they cannot take both. The answer to the question of who would take which, when given the choice, is complex because it involves dynamics (e.g., one’s previous choices regarding skill development may affect choices and choices change the skills individuals have). To predict this choice, I use a dynamic theory of self-regulation (Vancouver, 2008) with an emphasis on the expectancy theory (Vroom, 1964) component within it to argue that beliefs regarding learning and how learning will lead to valued outcomes plays a role in what individuals would do in this example. I also develop predictions regarding a contextual variable (i.e., the flexibility one has in determining one’s roles) and the individual difference variable, learning goal orientation, which is the degree to which one values learning generally (Dweck, 1986).

To test my predictions, I describe a study where role flexibility is manipulated and topic of study is the dependent variable. In addition, expectancy theory concepts and learning goal orientation are measured as predictor variables. In the sections that follow, I first review the importance of self-directed learning in organizational settings, followed by a definition and description of the importance of the situational context of role flexibility. I then describe expectancy theory as it has been conceptualized within self-regulation theory and the role of learning goal orientation with particular attention to its relevance to self-directed learning in a work context. This is followed by a description of a study to test the predictions.
Role of Self-Directed Learning in Organizations

In recent years, organizations have given individuals more autonomy, or control over certain tasks and dimensions, at work (Grant, Fried, & Jullierat, 2011). Along with this autonomy has been an expectation that individuals continuously improve as part of one’s day-to-day job (Parker et al., 1997). In today’s work environment, individuals are often responsible for their own education and learning (London, 2011). In fact, many researchers argue for a general action-oriented theory of how individuals act at work, rather than a passive or reactive-oriented approach (Crant, 2000). The increasing autonomy and reliance on continuous learning manifest for individuals in a couple of different ways. One way is that individuals have more autonomy in determining what to learn (called “self-directed learning”) and the other way is that individuals might have more say in determining what roles they are responsible for fulfilling (called “role flexibility”). Both self-directed learning and role flexibility are reviewed in the following sections.

Self-directed learning. Self-directed learning presumably stems from individuals evaluating learning needs, setting learning goals, and gathering resources (Knowles, 1975; Long, 1989). From an organization’s point of view, continuous self-directed learning can play a large role in an organization’s competitiveness and effectiveness (Frese et al., 1997; Goldstein & Ford, 2002; Kim, 1993; Senge, 2003; Sonnentag, 2003), because organizations evolve through the continuous learning of their employees (Conger & Xin, 2000; Goldstein & Ford, 2002; Noe, 1999; Reingold, 1997; Saari, Johnson, McLaughlin, & Zimmerle, 1988; Tsai, Yen, Huang, & Huang, 2007). Indeed, the current epoch of work is called “the Information Age,” as globalization, technology, and data
collection advance quickly (Bassi, Benson, & Cheney, 1996; Bjork, Dunlosky & Kornell, 2013; Cascio, 2003; Guglielmino & Guglielmino, 1988; London, 2011; London & Moore, 1999; Schein, 1993), and information is more readily available. To keep from becoming obsolete, organizations encourage their employees to partake in self-directed learning (Guglielmino & Guglielmino, 1994).

However, unlike organization-directed learning where there are methods for determining on what domains to focus (Goldstein & Ford, 2002), it is not clear how individuals determine where to focus their self-directed learning (Clardy, 2000; Parker, 2000). That is, most jobs have a set of dimensions pertinent to performing well at that job (Hough & Oswald, 2000). When following human resource management prescriptions, organizations select employees who are strong in the set of dimensions important to the job in question and train the knowledge and skills required (Kraiger, 2003). However, it is nearly always the case that individuals can become stronger in the dimensions they use for a job after individuals are hired (Parker, 2000). Additionally, maintenance of already strong job and career skills often involves long hours of deliberative practice, not merely experience doing the job (Ericsson & Charness, 1994; Ericsson, Krampe, & Tesch-Römer, 1993; Schein, 1993). For example, professional musicians spend hours a day practicing various aspects of their craft to remain competent (Sloboda, Davidson, Howe, & Moore, 1996). Assuming that individuals cannot allocate resources to every relevant dimension simultaneously, it becomes important to know how individuals determine where to focus resources on skill development and maintenance. This question is the central question addressed in this thesis.
Role flexibility. In some situations, individuals have input into which tasks or dimensions on the job are most important and also input into the process of completing those tasks (Ilgen & Hollenbeck, 1991). Allowing individuals this control over certain tasks and dimensions is autonomy. Autonomy for employees can include control over schedules, the tasks employees choose to do, control of free time, and work pace at the office (Adler, 1993). Moreover, some individuals have the opportunity to expand or reduce their different roles at work. If an individual has control over his or her roles, including control over what dimensions of the job are rewarded, this individual has high role flexibility. For example, the academic in the earlier example may potentially be able to elect which role (teaching or research) is more heavily rewarded. Moreover, academics may select which institutions to apply to on the job market based on which role is rewarded (i.e., only apply to institutions where research productivity is heavily emphasized, or institutions where instruction and teaching are heavily emphasized) as part of a self-selection process (e.g., Ryan, Sacco, McFarland, & Kriska, 2000). Of course, for some jobs and in some organizations, employees have little say over what they do or how rewards are allocated across one’s various roles (Deckop, Mangel, & Cirka, 1999). Using the academician example, if a university only rewarded those strong in both teaching and researching, the academic has less role flexibility in the situation, because the academic does not have a say in what is rewarded or has to reach multiple hurdles (i.e., standards) to achieve a promotion (Mendoza, Bard, Mumford, & Ang, 2004).

In the current thesis, I assume that individuals have control over what they learn, meaning individuals have the opportunity to direct their learning, because the focus of
this study is about how individuals make that choice. However, I do not assume that all
individuals have role flexibility. Some may and some may not. Yet, role flexibility is
likely important when an individual makes choices about what to learn. To understand
why that might be the case, and to provide a framework for understanding the choice
process more generally, I now turn to a theory of motivation called self-regulation theory
(Vancouver & Day, 2005) and expectancy theory (Vroom, 1964).

Self-Regulation and Expectancy Theory

Self-regulation theory is a theory of motivation that focuses on discrepancies
between current and desired states (i.e., goals) and the cognitive architecture that
motivates the reduction of positively signed discrepancies (Kanfer, 1990; Vancouver,
2008). Specifically, if one is at or beyond the goal, little to no goal-directed behavior
occurs. In contrast, if the desired state is beyond the current state, an individual is likely
motivated to act to reduce the discrepancy behaviorally (Diefendorff & Chandler, 2011).
Thus, discrepancies, which may be constantly changing over time, are a main factor in
determining action according to theories of self-regulation (Diefendorff & Chandler,
2011).

To some extent, discrepancy reduction via goal striving can occur in parallel. That
is, behaviors can positively affect multiple goals at once. However, often goals conflict
such that one cannot strive for or act toward one goal while striving for another goal.
Expectancy theory (Vroom, 1964) is a theory of choice and recently Vancouver et al.
(2010) incorporated expectancy theory into self-regulation theory to address how one
might resolve goal conflict (i.e., make choices among goals). Moreover, the integration of
expectancy theory with the architecture of control theory found in many self-regulation
theories increased the kinds of choices and contexts an expectancy theory approach could handle. In particular, it allowed for the understanding of nonlinear and dynamic reward contingencies like those associated with self-directed learning.

There are three beliefs central to expectancy theory: expectancy, valence, and instrumentality, which is why expectancy theory is sometimes called \textit{VIE theory} (Mitchell & Daniels, 2003). Expectancy is an individual’s belief about the level of effort needed to achieve a given level of performance, which is largely a function of that individual’s confidence or self-efficacy (Diefendorff & Chandler, 2011). That is, an individual’s confidence or self-efficacy is a type of expectancy (Bandura, 1977; Diefendorff & Chandler, 2011) and researchers commonly use self-efficacy to measure and evaluate an individual’s expectancy (i.e., Colquitt, LePine, & Noe, 2000).

Valence is the anticipated satisfaction (or dissatisfaction) with each outcome associated with the choice (Vroom, 1964). In Vroom’s original expectancy theory, valence indicates the anticipated value individuals placed in the outcomes accrued via completing an action (Kanfer, 1990; Vroom, 1964). Outcomes can be valued if they are intrinsically interesting or if they contribute to important goals for individuals (Eccles & Wigfield, 2002). That is, a task can have value if completing the task is a step towards a larger goal (e.g., a career goal). Valence is a subjective estimate of the desirability of the outcomes and can be positive or negative (Hackman & Porter, 1968). In expectancy theory, valences are weighted by instrumentalities (Vroom, 1964). These instrumentalities are beliefs in contingencies between outcomes. In organizational contexts, the primary outcome of interest is typically performance. Thus, instrumentalities refer to estimates of how likely secondary outcomes will be obtained if
the level of performance in question is achieved (Diefendorff & Chandler, 2011; Mitchell & Daniels, 2003; Vroom, 1964). Secondary outcomes can include pay, promotion, or knowledge gain, or negatively valenced outcomes like punishments. The sum of the valences weighted by their instrumentalities for all the outcomes determines the attractiveness of the option. Attractiveness is therefore the combined assessment of all positive and negative aspects of each outcome associated with the option. Attractiveness is multiplied by expectancy. This product determines the motivational force of the option. Individuals base choice on a comparison of motivational forces of the options. That is, expectancy theory is represented by the following equation that describes the role of each term used to present the motivational force of a behavioral option (Hackman & Porter, 1968; Vroom, 1964):

\[ MF = E \sum (I \times V) \]

In this equation, \( E \) is expectancy, \( I \) is instrumentality, and \( V \) is valence, where the latter two potentially refer to multiple outcomes. The equation indicates that the products of \( I \) and \( V \) for each outcome considered are summed and then multiplied by expectancy.

Vancouver et al. (2010) created a computational model of multiple-goal pursuit that formally (i.e., mathematically) describes how valences and expectancy are constructed and used for goal choice. In the multiple-goal pursuit model, valence is a function of the discrepancy of the individuals’ current state and desired state weighted by the importance of the goal and expectancy is a function of the resources the individual believes are needed and available to reduce the discrepancy (Vancouver et al., 2010).

The multiple-goal pursuit model makes three issues relevant to research on choice behavior. First, it makes relevant the construct of goals in relation to choice. Namely, the
multiple-goal pursuit model highlights that the goals relevant to an individual should be considered when predicting choice. Second, the multiple-goal pursuit model conceptualizes expectancies to be a function of the rate or effectiveness of action over time. Thus, it can be very useful for considering choices involving rates of change like learning. Finally, the theory considers the valence of a goal at any one time to be a positive function of the discrepancy or anticipated discrepancy from goals and the importance of achieving each goal. Because the motivation of discrepancies are often asymmetric (i.e., only positive discrepancies where a current or anticipated state is falling short of a desired state are motivating), choice predictions require considering current or anticipated conditions that relate to the goals of interest.

In the next section, I describe the goals that are likely relevant for the choice of what to learn in organizational settings, and in the process, outline the rest of the literature review.

**Goals of the Self-Directed Learner**

First and foremost, I assume individuals are interested in acquiring the rewards associated with performing (Deci, Koestner, & Ryan, 1999) and that individuals believe that the skills and knowledge related to the performance dimension are related to actual performance. Second, I assume that learning might be an intrinsic goal (Deci & Ryan, 1985), though of varying importance for different individuals (Brett & VandeWalle, 1999).

In terms of the first goal (obtaining rewards), the primary constructs likely to predict choice are the reward structure and the role flexibility situation, with a specific focus on expectancy for obtaining the reward. In terms of the second goal (enhancing
learning), the primary constructs likely to predict choice are the beliefs regarding expectancy for anticipated improvement (or anticipated ability to learn) and valence for learning or improving knowledge. The rest of the literature review is organized in terms of the two goals of the self-directed learner. First, I review research relevant to the goal of obtaining rewards. Second, I review research relevant to the goal of enhancing learning. Rates of learning, and beliefs about the rates of learning, are relevant and reviewed in this section. In this thesis, I refer to these beliefs about rates of learning as anticipated relative improvement. In addition, some individuals may also value enhancing learning more than other individuals. This concept, called learning goal orientation, is reviewed following anticipated relative improvement.

**Obtaining rewards.** Extrinsic rewards motivate behavior (Deci, Koestner, & Ryan, 1999; Gupta & Shaw, 2014; Jenkins, Mitra, Gupta, & Shaw, 1998). Some examples of extrinsic rewards are monetary gain and reputation or image (Vansteenkiste, Lens, & Deci, 2006; Wildman, Bedwell, Salas, & Smith-Jentsch, 2011). However, money is one of the most sought-after extrinsic rewards (Rynes, Gerhart, & Parks, 2005). Indeed, reward structures, or the performance criteria or standards that an individual needs to meet before being awarded something (Michaels, 1977), are often thought of in terms of monetary pay (Heneman, Ledford Jr., & Gresham, 2000). Extrinsic reward-earning typically involves receiving a reward outside of the immediate activity and is provided by someone else (Brief & Aldag, 1977; Schuler, 1975). However, the activities that are rewarded might be somewhat up to the individual employee. That is, in a flexible role environment, one’s rewards might be based on performance in one or more chosen
domains, whereas in a less flexible role environment, rewards might be based on performance across a given set of required domains.

In role flexible environments, choice of the domain(s) to focus behavior and learning is likely a straightforward function of expectancies. Expectancies are most important in this case because rewards would be more closely associated with the better expected performance, aligning valence of an option with the expectancies of the options. Evidence for this assertion appears in the self-efficacy literature. Self-efficacy is a construct typically equated with expectancy (e.g., Kirsch, 1985) because self-efficacy is a judgment of confidence in one’s ability to perform at a certain level in order for an outcome to occur (Bandura, 1977). Self-efficacy theory (Bandura, 1997) predicts that individuals will likely choose options for which one's expectancy or self-efficacy is high, provided the attractiveness of the outcomes associated with the option is positive (Bandura & Schunk, 1981; Colquitt et al., 2000; Compeau, Higgins, & Huff, 1999; Locke, Frederick, Lee, & Bobko, 1984). Moreover, self-efficacy has been shown to predict whether individuals select or accept training (Aguinis & Kraiger, 2009; Gist, Schwoerer, & Rosen, 1989; Hackett & Betz, 1995; Kraiger, 2003; Quiñones, 1997). For instance, computer efficacy determined whether or not college students chose to use computers in a training context (Hill, Smith, & Mann, 1987) and computer-related self-efficacy also determined whether individuals used technology during training (Colquitt et al., 2000; Salas & Cannon-Bowers, 2001).

The research described above suggests that individuals choose to work on what they think they are best at (Lent, Brown, & Larkin, 1986). In contexts where one has role flexibility, this positive effect for self-efficacy/expectancy likely translates into a choice
for one’s strength because such choices would increase the probability of obtaining rewards if rewards were tied to performance. Moreover, role flexibility would allow one to specialize on the job, increasing the probability that one would perform well and be rewarded. To increase specialization, additional training in the role would likely be sought. Thus, the domain(s) with the highest expectancies would be chosen over domains with lower expectancies. This assertion leads to my first hypothesis:

_Hypothesis 1: High role flexibility will positively predict choice of practicing a strength._

An exception to the above prediction might occur if the reward structure is nonlinear. That is, if individuals are rewarded for reaching some threshold level of performance, as opposed to being rewarded for the level of performance reached, then individuals who believe they could readily reach the threshold given current knowledge and skill might see little value in further developing knowledge and skill in that domain. In this scenario, individuals might see greater value in developing a weakness. Nonlinear reward systems are often advocated in organizational settings because organizations need employees to allocate resources across numerous organizational goals and the returns to organizations depend on the levels of performance on those goals (Pritchard, Paquin, DeCuir, McCormick, & Bly, 2002). Indeed, this is the premise of ProMES (Pritchard et al., 2002), which advocates developing reward systems that provide no more extra reward once a specified level of performance is reached. Likewise, many organizations or decision policies describe hurdles, or levels of performance, needed to obtain rewards like promotion or pay (Mendoza et al., 2004). For example, many academic departments have thresholds for publications needed to achieve tenure or to be considered for full
professor (Podsakoff, MacKenzie, Podsakoff, & Bachrach, 2008). It is just these types of systems where a multiple-goal-based motivational model is more applicable than a linear model where more is assumed to be better.

For example, consider a scenario where an individual does not have role flexibility. That is, the individual is expected to perform well in multiple domains. Additionally, assume that performance thresholds are held for each domain (i.e., rewards are allocated if and only if one performs above all the thresholds). In this situation, the self-regulation model of motivation would attach a higher value to the domain in which individuals feel they had the greatest discrepancy from the goal (i.e., threshold); that is, the relative weakness.

Evidence for this assertion comes from both the self-regulation and proactive behavior literatures. In self-regulation models, discrepancies between where an individual wants to be and where an individual currently is motivate behavior (Vancouver & Day, 2005). That is, individuals are more likely to choose goals with greater discrepancies (Vancouver et al., 2010) and are more motivated to reduce these discrepancies once a goal has been chosen (Vancouver, 2005; Vancouver, More & Yoder, 2008). For example, researchers who studied information seeking processes over time discovered that individuals seek knowledge about areas in which they know the least, and that as they learn, they seek information less, creating a negative relationship between time and information seeking (Bauer et al., 2007; Chan & Schmitt, 2000). These predictions are also consistent with the literature on proactive information seeking (Crant, 2000; Miller & Jablin, 1991; Morrison, 1993). This research supports the notion that discrepancies
drive information seeking behavior. That is, in these studies, individuals focused resources towards getting information concerning the areas they knew the least about.

All of the above discussion is directly relevant to the low role flexible situation where multiple goals are more likely to be relevant. That is, if an individual is in a low role flexible situation, the individual would focus resources towards an area of relative weakness. This is the logic behind Hypothesis 2.

**Hypothesis 2:** Low role flexibility will positively predict choice of practicing a weakness.

The role and external reward structures are contextual elements in the choice process. However, individuals are also motivated by intrinsic rewards such as increasing knowledge (Deci & Ryan, 1985). The importance of learning and one’s belief regarding when more learning would be expected are also likely important when considering the choice of where to direct learning. I discuss these elements next.

**Enhancing learning.** In terms of the second goal of the self-directed learner, enhancing learning, the primary constructs likely to predict choice are beliefs regarding how much effect a learning choice will have on knowledge and skills and the importance or desirability of learning. In particular, beliefs about rates of learning are likely to play an important role. However, learning rates are a complex notion in psychology and potentially complex in the minds of students and employees. Thus, I begin this section with a description of research about learning rates.

**Learning curves and anticipated relative improvement.** Learning follows a curve (Carlson, 1973; Ebbinghaus, 1885/1964; Ohlsson, 1996; Yelle, 1979). That is, as individuals develop knowledge and skill, sometimes progress is relatively fast and
sometimes it is relatively slow. Moreover, individuals have varying beliefs about how quickly learning occurs as a function of one’s current skill level (Tenbrink et al., 2011). If individuals are comparing improving on a relative strength to improving on a relative weakness, there may be variability in the believed rates of improvement of strengths and weaknesses or what this thesis calls “anticipated relative improvement.” This variability in anticipated relative improvement can be captured in the learning curve concept.

Technically, learning curves depict the overall trends of error detection and remedy (aka learning) over time (Hirschmann, 1964; Ohlsson, 1996). There are five well-known learning curve models: the log-linear model, the plateau model, the Stanford-B model, the DeJong model, and the S-model (Yelle, 1979). For example, the Stanford-B model (Figure 1) has a steep positive slope that plateaus at the peak of learning (Ebbinghaus, 1964; Ohlsson, 1996). This model indicates that a lot of learning, or error detection, happens during the beginning of learning and eventually slows down.
Ackerman (1987) studied individual differences in task acquisition and found asymptotic learning curves similar to the curve represented in the Stanford-B model. He found asymptotic learning curves to be especially true for “closed” domain-specific tasks, like addition, multiplication, or learning a set of facts. For example, once a person has learned the principles of addition, there is no more for this individual to learn (Ackerman, 2007). This effect was also found in ratings of teachers who teach a particular course (Hanges, Schneider, & Niles, 1990), motor skills research (Farrel & McDaniel, 2001), and other “closed” topics (Ackerman, 2007).

In contrast, the DeJong learning curve (see Figure 2) describes learning as initially slow and taking a lot of effort at first before speeding up as knowledge is accumulated. With this learning curve, individuals will make the most progress learning about something in which they already have some proficiency. This type of learning
curve results in a phenomenon called the Matthew effect (Merton, 1968). The Matthew effect is also described as a “fan-spread” effect in education and learning (Walberg & Tsai, 1983). In the learning context, individuals who initially score high will gain more from a subsequent learning experience than individuals who initially score low (Cook et al., 1979; Walberg & Tsai, 1983). This learning curve and the Matthew effect was found on more “open” topics, such as scientific knowledge (Walberg & Tsai, 1983) and vocabulary acquisition (Penno, Wilkinson, & Moore, 2002). In contrast to closed topics, an individual could never learn everything with regards to an open topic. Once the individual masters a concept related to the topic, that concept builds upon the next concept and this pattern continues (Ackerman, 2007).

Figure 2. The DeJong model.
If an individual believes in the asymptotic effect, the individual believes he or she will gain the most knowledge from studying a weakness, because a weakness will show the most improvement. If an individual believes in the Matthew effect, the individual believes he or she will gain the most knowledge from studying and training a strength, because a strength will show the most improvement. If one is thinking about the goal of enhancing learning, anticipated relative improvement could be an important variable to consider. That is, from an expectancy theory perspective one would expect, all else being equal, that one would study the topic expected to lead to the greatest amount of learning. For those holding to the asymptotic view, this would be one’s weakness. For those holding to the Matthew effect view, this would be one’s strength. Translating this concept into a hypothesis leads to the following:

*Hypothesis 3: Anticipated relative improvement belief will predict study topic choice. Belief in the Matthew effect will predict choice of practicing a relative strength for individuals. Belief in the asymptotic effect will predict choice of practicing a relative weakness for individuals.*

In sum, it is possible that what one chooses to learn will be somewhat based on the desire to enhance one’s learning. The degree to which individuals believe they will improve their learning might depend on the learning curve they think is applicable and on their belief in their current state of knowledge (i.e., strengths and weaknesses).

*Individual difference in value of enhancing learning: Goal orientation.*

According to both VIE theory and the dynamic self-regulation theory, individuals take into account their own expectancy, but also take into consideration how desirable outcomes (the result of their actions) are expected to be. The desirability of enhancing
learning is related to and may be a function of an individual difference called goal orientation (Dweck, 1986). Learning goal orientation deals with the importance individuals place on learning or mastering a topic. Some individuals are more interested in learning and mastery than others and have higher propensities to seek information than others (Brett & VandeWalle, 1999). Individuals may choose different areas to focus resources (i.e., relative strengths or weaknesses) due to the degree to which enhancing learning is desirable. Therefore, it becomes important to consider the valence of enhancing learning in terms of a relevant individual difference construct (Latham & Pinder, 2005), which is learning goal orientation.

Goal orientation is considered a stable individual difference trait that affects what types of goals individuals adopt based on the desirability of the goals (DeRue et al., 2012). Specifically, individuals who have a high learning goal orientation focus on improving, which suggests that enhancing learning is likely to be a more desirable goal for these individuals than individuals low on learning goal orientations (Brett & VandeWalle, 1999; Dweck, 1986; Kraiger, 2003; VandeWalle, Brown, Cron, & Slocum, 1999; Yi & Hwang, 2003), because the learning goal orientation is characterized by a focus on mastery and improving competence (Ford, Smith, Weisbein, Gully, & Salas, 1998; Deci & Ryan, 2000). For example, in one study, goal orientations of participants partially determined the content of their goals in a training program context. Those highest in a learning goal orientation picked goals that involved elements of mastery and skill improvement (Brett & Vandewalle, 1999). Researchers also found that those with a high learning goal orientation had high motivation in a classroom setting (Klein, Noe, & Wang, 2006). Those who score highly in a learning goal orientation not only seek more
challenging tasks, but also are more likely to seek feedback or information than those who score highly in other types of goal orientations (VandeWalle & Cummings, 1997; VandeWalle et al., 2001).

Goal orientation appears to be an individual difference variable that might affect how individuals guide their self-directed learning. That is, those with a high learning goal orientation would be more likely to focus on that which can be improved more. Yet, as mentioned above, individuals may have different beliefs about what can be improved more. If learning goal orientation is essentially how important the goal of enhancing learning is to an individual, then it seems as if learning goal orientation and anticipated relative improvement may interact. That is, those who have a high learning goal orientation may be more likely to use anticipated relative improvement in their decision-making than those who do not have a high learning goal orientation. Indeed, the formula for expectancy theory includes multiplicative interaction terms between valence and expectancy (Vroom, 1964). Therefore, if an individual does not have a positive or negative valence for an outcome, the individual’s expectancy would not matter (even if expectancy was high), because expectancy is multiplied by valence. In considering enhancing learning, if an individual had a high learning goal orientation, the individual would allocate resources to the area that would improve more, which is governed by the anticipated relative improvement belief. Therefore, I predicted a two-way interaction between learning goal orientation and anticipated relative improvement.

**Hypothesis 4**: Learning goal orientation and anticipated relative improvement will interact such that anticipated relative improvement has a higher likelihood of predicting choice in cases of higher learning goal orientation.
Current Study

The overall learning decision model introduced in this paper is complex, made more so by the overlap and relationships between variables. For instance, the reward structure is a contingency for how role flexibility may influence learning choice. The goal of the current study was to manipulate an important variable, which is role flexibility, and measure anticipated relative improvement and learning goal orientation. In this study, I keep the reward structure constant.

The current study investigated resource allocation to learning in the context of a trivia game, in which half of participants were able to pick the topic on which they were quizzed and the other half of participants were quizzed on both topics. This manipulation was a manipulation of role flexibility. Both anticipated relative improvement and learning goal orientation were measured. Role flexibility, anticipated relative improvement, and learning goal orientation were hypothesized to determine if individuals focused on increasing or maintaining knowledge about strengths or improving knowledge about weaknesses. The primary dependent variable was choice of topic of study. All participants were given the opportunity to practice either of two areas pertaining to the trivia game, after they had feedback indicating which was their relative strength and which was their relative weakness. This feedback was designed to not only differentiate a strength and a weakness, but also to provide information that the level of knowledge for the strength was likely above the threshold needed to achieve the reward whereas the level of knowledge of the weakness was below the threshold. These threshold levels allowed for the examination of the nonlinear elements of the self-regulation theory.
Method

Participants

A total of 176 participants (63.7% female, mean age in years = 19.38) were recruited from undergraduate psychology courses. Participants received partial credit in their psychology courses for participation in experiments. Before the study began, participants read and signed a consent form. A total of five ($N = 5$) participants were removed from the study due to written or oral suspicion of false feedback.

Task

The task was a trivial pursuit task involving two topics: “Science and Nature” and “Arts and Entertainment.” Participants took a practice quiz on a computer to see where they scored on each of the two categories. Questions were taken from various Trivial Pursuit board games.

Measures and Manipulations

Expectancy/valence. Participants answered a series of questions indicating their expectancy and valence for the two trivial pursuit topics. Expectancy was assessed by asking the percentage participants expected to answer correctly on a quiz in either category. For the valence questions, participants indicated how much they valued the trivial pursuit topics and also how much they valued classes in science and classes in art.

Strength/weakness manipulation. Participants received manipulated feedback at the end of a practice round of the trivial pursuit quiz task. In the category on which a participant did better, the computer indicated that he or she got 85% of the questions correct. In the category on which the participant did worse, the computer indicated that he or she got 64% of the questions correct. This feedback was predetermined. For those
participants who got an equal number of items correct in both categories, the computer randomly determined on which topic the individual was told he or she got the 85% and 64% correct.

To check the manipulation, participants answered a short survey about the topics on which they had received feedback. Specifically, they rated the likelihood (yes or no) that they would achieve each of 5 levels of performance (20%, 40%, 60%, 80%, and 100%) on a subsequent quiz if taken again immediately and if taken after 20 minutes of studying the topic. Participants also indicated on a 1-5 scale (1 – not at all to 5 – extremely) how capable they were of reaching each level of performance. Participants also answered: “After the practice round at the beginning, which topic did the computer tell you was your relative strength?”, questions asking participants what scores they had obtained in each topic, and a question asking whether they had chosen to study their relative strength or their relative weakness before the final quiz task.

**Anticipated relative improvement.** Participants answered a series of questions about whether they believed in the asymptotic effect, a linear effect, or the Matthew effect to determine their beliefs about how relative differences in current knowledge affected their likely knowledge gain if they studied a topic. The set of questions was about the topics in the trivial pursuit game. That is, the questions asked “How much do you think you can improve your knowledge of the category ‘Science and Nature’ in 20 minutes?” and “How much do you think you can improve your knowledge of the category ‘Arts and Entertainment’ in 20 minutes?” For these questions, participants indicated the amount they believed they could improve using a 101 point slider scale (0 - cannot improve at all to 100 - can improve a great amount). To calculate anticipated
relative improvement, the rating given for improving the topic that was a weakness was subtracted from the rating given for improving the topic that was a strength. A positive score meant that the individual believed he/she could improve a strength more than a weakness (i.e., the Matthew effect). A negative score meant that the individual believed he/she could improve a weakness more than a strength (i.e., the asymptotic effect). A score at or near zero meant that the individual believed he/she could improve a strength and a weakness in equal amounts (i.e., the linear effect). Therefore, this particular anticipated relative improvement variable was coded as both a continuous and a categorical variable. Because this notion of beliefs about how relative current knowledge affects relative improvement has not been measured before, I included other items to assess this construct. These items and the results found for them are presented in Appendix A.

**Learning goal orientation.** Participants took a modified version of the scale developed by VandeWalle (1997) as a measure of learning goal orientation. This instrument has five Likert-type items geared towards assessing learning goal orientation. The scale ranged from 1 (strongly disagree) to 7 (strongly agree). VandeWalle (1997) found a Cronbach’s alpha of .88 and a test-retest reliability of .66 over a three month period. I made a few modifications to the scale to make it more relevant for the sample. Specifically, I added “or school” every time “work” was mentioned in the questions. Also, in one of the items that says “coworkers,” I added “or class peers”. This scale was edited in the past by researchers to accommodate specific settings, like a college-level statistics class (Beck & Schmidt, 2013). Some example items from the scale are: “I am
willing to select a challenging work or school assignment that I can learn a lot from” and “I often look for opportunities to develop new skills and knowledge.”

**Role flexibility manipulation.** Participants were randomly assigned to one of two role flexibility conditions. In the high role flexible condition, participants were told they could choose the topic of a final trivial pursuit quiz. They were also told that they needed to achieve 80% on just that topic to be awarded $5. In the low role flexible condition, participants were told they would be quizzed on both topics and that they needed to achieve an 80% on both topics to be awarded $5. To check this manipulation, participants were asked after the final trivial pursuit quiz whether or not they had a choice in the topic.

**Self-directed learning choice.** Participants were asked to pick which of the two trivial pursuit categories they would like to study before the final quiz task.

**Additional measures.** Performance was measured by how many questions participants answered correctly. Also, an open-ended essay question asked participants to describe their decision-making process for choosing what to study. Finally, participants were asked to report their age, gender, racial/ethnic background, year in school, and work experience.

**Procedure**

Participants read and signed a consent form. Participants read instructions about the trivial pursuit quiz in which they were to take part. They then took a practice question with fourteen questions from each topic. Their performance on this practice quiz was used to determine the feedback they received on each topic (see strength/weakness manipulation above). Next, the instructions told participants how they might receive $5
as compensation for a final quiz performance, depending on role flexibility condition to which they were assigned randomly using a block randomization design. Participants also read that they would be able to study questions in one of two categories (“Science and Nature” or “Arts and Entertainment”). The participants were then given expectancy manipulation check, anticipated relative improvement, and learning goal orientation items.

Following the measures, participants had the opportunity to practice and review the topic of their choosing for 20 minutes. For this review session, participants determined which of the two categories they wanted to study. After the 20-minute review session, participants in the high role flexible condition took a quiz on their chosen topic. Those in the low role flexible condition took a quiz on both topics. Either way, the quizzes included 20 items. For those in the high role flexible condition (i.e., participants chose the topic of the quiz), participants answered 20 questions in one of the two categories and needed to achieve at least 80% overall. In the low role flexible condition, participants answered 10 questions from each category and needed to achieve at least 80% on both topics. Similar to the practice quiz, each question during the study session and each question on the final quiz had four multiple-choice options for answers. The review session questions included most, but not all, of the final quiz questions. At the end of the final quiz, the computer scored each participant and if the participant got at least 16 questions correct, which was the criteria for scoring an 80% on the quiz, he or she received $5. For those participants in the low role flexible condition, the computer multiplied the number of answers they answered correctly on the category that was their strength by two, to ensure fairness in compensation between the two conditions.
However, participants in the low role flexible condition did not know that the computer calculated their reward potential in this manner. After the quiz was over, participants completed the remaining manipulation checks. They also answered the open-ended decision-making process question. Participants who scored well enough to make the money were paid and all participants were debriefed and thanked.

**Data Analysis and Coding**

The analysis of the current study involved conducting a logistic regression analysis with multiple predictors (role flexibility, anticipated relative improvement, and learning goal orientation) and a binary (study topic choice – strength or weakness) criterion variable. Role flexibility was coded “0” for high role flexibility and “1” for low role flexibility. When anticipated relative improvement was coded as a categorical variable, belief in the asymptotic effect was coded as “1”, meaning the individual indicated that a weakness would improve more than a strength in 20 minutes, belief in the linear effect was coded as “2”, meaning the individual indicated that a weakness and strength would improve the same amount in 20 minutes, and belief in a Matthew effect was coded as “3”, meaning the individual indicated that a strength would improve more than a weakness in 20 minutes. The criterion variable was coded “0” for strength and “1” for weakness.
Results

Manipulation Checks

Based on the role flexibility manipulation check item, 71.3% of participants correctly indicated their assigned role condition. However, almost all the incorrect answers came from individuals who were in a low role flexible condition saying they had a choice in the quiz topic. Likely, these individuals misinterpreted the question because they had a choice in what topic to study.

To confirm that the manipulated strength and weakness feedback was believable, frequencies were run on expectancies for individual strengths and weaknesses both before and after the manipulated feedback. Before the feedback, 49.7% of individuals expected to perform best on a quiz about the topic on which they performed best (or the topic the computer assigned as their strength) and 43.9% of individuals expected to perform best on a quiz about the topic on which they performed worse (or the topic the computer assigned as their weakness). Only 6.4% expected to do equally well on a quiz about their strength and a quiz about their weakness. After the feedback, 67.8% of individuals expected to perform best on a quiz about the topic that was their strength (as opposed to their weakness), 17.0% of individuals expected to perform best on a quiz about their weakness, and 15.2% expected to do equally well on either topic. A paired samples t-test was run on after-feedback performance expectancies to see if individuals expected to perform better on a quiz about their strength than on a quiz about their weakness. There was a significant difference between expectancy for performance on a quiz about strengths (M = 12.16, SD = 3.26) when compared to the expectancy for performance on a quiz about weaknesses (M = 10.12, SD = 3.03), t(170) = 8.40, p < .001,
$d = .649$. Specifically, individuals had higher expectancy for their strengths than their weaknesses after receiving the practice quiz feedback.

Additionally, a paired samples $t$-test was run on the manipulation check questions asking individuals what percentage the computer told them they obtained on each topic. There was a significant difference between reported percentage for strength ($M = 80.53$, $SD = 9.58$) and reported percentage for weakness ($M = 61.70$, $SD = 8.87$), $t(170) = 19.05$, $p < .001$, $d = 2.04$. These means also closely paralleled the feedback of 85% and 64%, respectively. Lastly, a manipulation check asking the individuals whether they chose to study a relative strength or relative weakness was compared to their choice. A total of 10.5% of individuals indicated a choice inconsistent with the feedback they received and the choice they made. All in all, these results suggest that the relative strength/weakness manipulated was successful. Nonetheless, the hypotheses were tested three different ways to take into account the individuals that responded in ways that were inconsistent with manipulations. In the first way, statistical tests of the hypotheses were analyzed based on the feedback the computer gave participants (i.e., the manipulated conditions). Second, only the individuals (67.8%) who believed the feedback according to the expectancy manipulation check were analyzed. These analyses are presented in Appendix B. Third, only those individuals (89.5%) who correctly indicated that they picked a strength or weakness in agreement with the computer feedback (according to the question “Did you choose to study the topic that was your relative strength or your relative weakness?”) were analyzed. For these analyses, see Appendix C.
Descriptive Statistics

Descriptive statistics were separated by role flexibility condition. Among the individuals in the low role flexible condition, 21.7% chose to study a strength and 78.3% chose to study a weakness. Among the individuals in the high role flexible condition, 75% chose to be quizzed on their strength and 25% chose to be quizzed on their weakness. Additionally, 70.5% of individuals chose to study a strength and 29.5% of individuals chose to study a weakness in the high role flexible condition. See Figure 3 for a graphical representation of the marginal relationships between the categorical predictor and the criterion variable.

Figure 3. Proportion of individuals choosing to study weakness versus strength depending on role flexibility condition.
Descriptive statistics were separated by anticipated relative improvement belief as well. Among the individuals who believed in the asymptotic effect, 36% chose to study a strength and 64% chose to study a weakness. Among the individuals who believed in the linear effect, 75% chose to study a strength and 25% chose to study a weakness. Among the individuals who believed in the Matthew effect, 45.4% chose to study a strength and 54.6% chose to study a weakness. See Figure 4 for a graphical representation of the marginal relationships between the categorical predictor and the criterion variable.

![Figure 4](chart.png)

*Figure 4.* Proportion of individuals choosing to study weakness versus strength depending on anticipated relative improvement belief.

**Omnibus Test**

I conducted an omnibus test to examine the overall effect of role flexibility (high versus low), anticipated relative improvement (belief in asymptotic effect versus linear...
effect versus Matthew effect), and learning goal orientation as predictors of topic chosen to study. For the whole model, the chi-square statistic in the first block verified that the model with the predictors was a better fitting model than the null model, $\Delta \chi^2(4, N = 171) = 56.89, p < .001$, Nagelkerke $R^2 = .38$ (see Table 1). That is, as a set, the predictors were significantly related to study topic choice.

Table 1

<table>
<thead>
<tr>
<th>Variable</th>
<th>$B^a$</th>
<th>$X^2_{Wald}$</th>
<th>OR</th>
<th>$\Delta \chi^2_{LR}$</th>
<th>$\Delta R^2_{Nagelkerke}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Role Flexibility$^b$</td>
<td>2.44</td>
<td>37.21**</td>
<td>11.44</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ARI$^c$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asymptotic Effect Belief</td>
<td>1.06</td>
<td>5.86*</td>
<td>2.88</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LGO</td>
<td>-0.02</td>
<td>0.01</td>
<td>0.98</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Step 2</td>
<td></td>
<td></td>
<td></td>
<td>1.08</td>
<td>0.01</td>
</tr>
<tr>
<td>ARI X LGO</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. $N = 171$. Strength was coded as “0” and weakness was coded as “1”. ARI = anticipated relative improvement. LGO = learning goal orientation.

$^a$Estimated regression coefficients at entry.

$^b$Role flexibility was coded as “0” = high role flexibility and “1” = low role flexibility.

$^c$Anticipated relative improvement was dummy coded with Matthew effect belief as the reference level.

$p < .05$. $**p < .01$.

Hypothesis Tests

Hypothesis 1 stated that high role flexibility would positively relate to choosing a strength. When role flexibility was high, the odds of individuals choosing to study a strength over a weakness were 11.49 times greater than when role flexibility was low,
Hypothesis 2 stated that low role flexibility would positively relate to choosing a weakness. As predicted, low role flexibility increased the odds of individuals choosing to study a weakness over a strength by 11.44 times, \( \text{Wald } \chi^2(1, N = 171) = 37.21, p < .001 \) (see Table 1) in the presence of the other predictors. These results strongly support Hypothesis 2.

Hypothesis 3 stated that belief in a Matthew effect would positively relate to choosing to study a strength and that belief in an asymptotic effect would positively relate to choosing to study a weakness. Anticipated relative improvement was tested as both a categorical variable (see Method section for coding) and a continuous variable. As a categorical variable, anticipated relative improvement related to study topic choice in the presence of the other predictors, \( \text{Wald } \chi^2(2, N = 171) = 12.36, p < .001 \) (see Table 1). I made pairwise comparisons using the Holm (1979) procedure to control for family-wise Type I error rate. When individuals believed in the asymptotic effect, the odds of individuals choosing to study a weakness over a strength were 2.88 times greater than for individuals who believed in the Matthew effect in the presence of all other predictors, \( \text{Wald } \chi^2(1, N = 171) = 5.86, p = .015 \) (see Table 1). That is, individuals were more likely to choose to study a weakness when they believed in the asymptotic effect and were more likely to choose to study a strength when they believed in the Matthew effect. No other pairwise comparisons were significant. These results support Hypothesis 3.

I also analyzed the data using anticipated relative improvement as a continuous variable. In that case, anticipated relative improvement did not significantly predict study
topic choice. This result is likely because those believing in a more linear effect overwhelmingly chose to study a strength (see Figure 4).

Hypothesis 4 predicted an interaction between anticipated relative improvement and learning goal orientation ($M = 5.33, SD = .87$). The interaction between anticipated relative improvement and learning goal orientation did not predict study topic choice, $Wald \chi^2(2, N = 171) = 1.71, p = .425$ (see Table 1), in the presence of the other predictors. The results do not support Hypothesis 4.
Discussion

Although individuals are encouraged to self-direct their learning on a daily basis at work due to the benefits learning provides organizations (DeRue, Ashford, & Myers, 2012; Frese, Fay, Hilburger, Leng, & Tag, 1997; Goldstein & Ford, 2002), little research has examined the factors that influence individuals’ choices of what to learn (Clardy, 2000). The purpose of the current study was to predict learning choice using expectancy theory (Vroom, 1964) and a dynamic model of self-regulation (Vancouver, 2008) incorporated in a multiple-goal pursuit model (Vancouver et al., 2010). In the following sections, I discuss the theoretical implications of the results, limitations of the current study, future directions, and practical implications.

Theoretical Implications

In the current study, I used a multiple-goal pursuit model (Vancouver et al., 2010) to predict how individuals would allocate resources toward learning. Specifically, this multiple-goal pursuit model makes use of expectancy theory (Vroom, 1964), which is a theory focused on how individuals make choices, and a dynamic self-regulation theory (Vancouver, 2008), which is a theory focused on motivation and goal pursuit. The multiple-goal pursuit model assumes individuals are pursuing multiple goals and highlights the importance of goals in decision-making. In this thesis, I predicted that individuals may have two salient goals when determining where to self-direct learning: obtaining rewards and enhancing learning. There was evidence in the current study that individuals were pursuing these two goals. In particular, individuals made choices consistent with both the goal of obtaining rewards and the goal of enhancing learning.
Regarding the goal of obtaining rewards, individuals made choices that maximized the chance of obtaining rewards. For example, individuals who were able to choose the ultimate quiz topic most frequently chose to study and be quizzed on a strength. That is, most individuals chose to be quizzed on and also chose to study the topic for which they had the higher expectancy of obtaining rewards. Individuals who were quizzed on both topics most frequently chose to study a weakness. In this case, individuals chose to study the topic for which their knowledge needed to be boosted in order to obtain the reward.

Regarding the goal of enhancing learning, some individuals also made choices that maximized learning. In particular, choice of topic to study was somewhat a function of which topic they thought they would improve upon the most. That is, if one thought a strength may improve more than a weakness as a function of studying, one was more likely to choose to study a strength. Likewise, if one thought a weakness may improve more than a strength while studying, one was more likely to choose to study a weakness. This finding also highlights the importance of beliefs in rates of change and how those beliefs will vary by individual. For instance, some individuals felt that knowledge begets increased knowledge (i.e. Matthew effect; Walberg & Tsai, 1983) and some individuals believed in diminishing returns (i.e. asymptotic effect; Ackerman, 2007). Indeed, of the 21.7% of individuals who chose to study a strength in the low role flexible condition, 66.7% believed in the Matthew effect, 33.3% believed in the linear effect, and none believed in the asymptotic effect, implying that the choice may have been guided by the goal of enhancing learning.
The multiple-goal pursuit model not only emphasizes that individuals pursue multiple goals but also that there are desired levels for those goals (Vancouver et al., 2010). The current study was designed to highlight the issue of desired levels by creating a specific reward level threshold. In particular, the reward was given based on achieving at least an 80% in the category of an individual’s choice for those in the high role flexible condition. Given that the feedback from the practice test regarding one of the topics was 85%, individuals could infer that they could obtain the reward without enhancing learning in their strength. Thus, it is not surprising that a handful of individuals (4 individuals) studied their weakness, even though these individuals picked their strength on which to be quizzed. Of course, individuals did not have much cushion on their strength. Indeed, on average, individuals thought that the computer feedback about their strength was 80.53% (see Results). Therefore, most individuals preferred to reinforce their strength, possibly because these individuals may not have thought that their practice test would accurately predict performance on the final quiz.

Likewise, when role flexibility was low, 78.3% of individuals chose to study a weakness. This result is strong evidence for the multiple-goal pursuit model, because the feedback (i.e., 64% on one of the topics) indicated that individuals were far from the goal level (i.e., 80%) and the context required that they pay attention to goal level to obtain the reward. In particular, self-regulation theory would predict that discrepancies are drivers of behavior (Vancouver, Tamanini, & Yoder, 2010). Therefore, many of the predictions of the multiple-goal pursuit model were supported in the current study. In the next section, limitations of the current study are reviewed, as well as avenues of future research.
Limitations and Future Research

All research has limitations and in the case of the current study there are limitations with regards to construct, internal, and external validity. For example, the construct validity issues of the current study may partially explain the lack of support for Hypothesis 4. Specifically, I found no interaction between anticipated relative improvement and learning goal orientation. Anticipated relative improvement may have had a construct validity problem while learning goal orientation may not have had sufficient variance due to the sample used. First, the concept of anticipated relative improvement was a new construct. To my knowledge, there are no existing scales that measure anticipated relative improvement. Therefore, I created six sets of items to try to accurately measure this concept. As indexed in Appendix A, these measures did not exhibit adequate psychometric qualities (e.g., the reliability was poor). For this reason, I only used the set of items specifically asking about the trivial pursuit task that allowed for both continuous and categorical scores. Unfortunately, results for anticipated relative improvement were only consistent with hypotheses using the categorical coding scheme. Future research should examine how to best measure the construct.

Second, the learning goal orientation scale used may have resulted in a ceiling effect due to the student sample of the current study. The mean for learning goal orientation was high relative to the top boundary (i.e., 5.33 on a 7-point scale) and the standard deviation was relatively small (i.e., .87), meaning there was not much variability on learning goal orientation. Indeed, no individual averaged below a “3” on the five items for learning goal orientation on the 7-point scale and learning goal orientation had a negatively skewed distribution ($G_7 = -.513$). Therefore, this ceiling effect may have made
finding an interaction between learning goal orientation and anticipated relative improvement less likely. Participants in this experiment were college students and may have had high scores on learning goal orientation due to the demand characteristics of the college environment and experimental setting (Orne, 1962). That is, individuals taking college classes might think they should report learning as being very important in experiments or, potentially, individuals in college may actually view learning as more important than individuals not in college. Individuals in organizations may be less likely to answer similar learning questions based on demand characteristics and/or may have more variability in the importance they place on learning. Therefore, conducting similar studies in applied settings may lead to the hypothesized results of the learning goal orientation variable.

A limitation of the current study related to internal validity is the manipulation of expectancy and relative strength. The topic that was considered the strength was not manipulated by random assignment, which may be a threat to internal validity. In particular, the number of individuals in each group were not equal (i.e., 71.9% of individuals were stronger in the Science and Nature category and 28.1% of individuals were stronger in the Arts and Entertainment category). Therefore, it is possible that the results could partially be attributed to some aspect of the Science and Nature category not present in the Arts and Entertainment category or attributed to individual differences between those individuals stronger in Science and Nature and individuals stronger in Arts and Entertainment. However, because this aspect of the experiment was a within-subject manipulation (i.e., every individual was assigned a relative strength and a relative weakness and the strength was one topic while the weakness was the other topic), it is not
likely that an individual difference confound would be of any concern. Additionally, an advantage of using non-random manipulated feedback is increased believability of the feedback. Some individuals may have known which of the two categories was stronger for them and random assignment may have contradicted their intuition which could have caused bigger internal validity issues. Despite increasing the believability, 17.0% of individuals did not believe or agree with the feedback concerning which topic was their strength and which was their weakness. This manipulation check led to an analysis of the results in multiple different ways. Although there is evidence that the manipulation worked for many, future studies may want to more extensively pilot test topics for the methodology and/or randomly assign which topic is a participant’s strength versus weakness to investigate if similar results would be obtained. If random assignment were to be done, researchers should choose topics that many individuals do not have much experience with ahead of time so few individuals would enter the study with preconceived notions. These solutions may eliminate problems of manipulated feedback in future studies.

To address external validity issues, I cover four issues that might be addressed with future research. First, it might be important to consider more goals that may be relevant in other types of settings. The current study focused on two goals in the context of a quiz. The two goals were obtaining rewards and enhancing learning. However, there may be more than two important goals in other contexts. For instance, in a teaching context, a third goal may be a reputational or image goal. To give an example, professors may want to appear competent and answer questions adequately to gain the trust and respect of their students. A potential way to measure the importance of this reputational
or image goal would be by measuring avoiding goal orientation. When individuals have a high avoiding goal orientation, they select goals that will aid them in avoiding negative consequences and judgments, like looking foolish (VandeWalle, Cron, & Slocum, 2001). Those who have a high avoiding goal orientation seek feedback less often (Edmonson, 1999; Levy, Albright, Cawley, & Williams, 1995). Therefore, if a reputational goal is a salient goal for individuals, they may prefer to improve in areas that preserve or increase their reputation. Future research could investigate the multiple-goal pursuit model’s ability to predict learning choice given three goals (i.e., obtaining rewards, enhancing learning, and preserving reputation) using a public speaking context as the final task and scores on avoiding goal orientations as a measure of the importance of preserving reputation. Just as it would be important to change the study task when there is a third possible goal involved, future studies should investigate resource allocation to self-directed learning with other tasks more generalizable than a trivia quiz task. Although some occupations may have specific sub-categories of knowledge that are important for the job, future studies should create paradigms that imitate or are more similar to actual tasks performed in specific occupations.

Second, the current study focused on a particular reward threshold (i.e., 80%) to test the asymmetric aspect of the multiple-goal pursuit model, but other reward thresholds should be investigated in future research. Researchers may want to increase the negative discrepancy and/or suggest that past performance precisely predicts future performance in order to further examine the multiple-goal pursuit model in terms of different thresholds. For instance, if the threshold for a final quiz task is 70% and individuals are told they achieved 95% on their topic of strength in the practice quiz, or are also told performance
on the practice quiz is highly predictive of performance on the final quiz, self-regulation theory would suggest that many more individuals would choose to be quizzed on their strength but ultimately choose to study their weakness.

Third, the reward structure used in the current study is one of a few possible reward structures that organizations may use to reward employees (Aguinis, 2009; Martocchio, 2011; Osterlog & Frey, 2002; Schmitt & Kemper, 1996). In the current study, I used a step function of rewards. In this structure, rewards are little to nothing unless the goal is reached (Schmitt & Kemper, 1996). The nature of the step function of rewards seems to highlight the goal of reaching the threshold because an individual will only get paid after reaching the threshold. In this context, the factors involved in obtaining rewards may overshadow factors involved in enhancing learning. An important question for future research may involve examining the learning choice in the context of other reward structures.

For instance, there is also the linear function of rewards that involves being rewarded consistently based on consistent performance or being rewarded consistently for every increasing level of performance reached (Schmitt & Kemper, 1996). If individuals get paid according to level of performance (e.g., paid based on percentage obtained on a test) or increasing levels of performance (e.g., paid based on percentage increased from a practice test to a final test), individuals may be inclined to choose strengths or weaknesses for resource allocation depending on their beliefs regarding enhancing learning. That is, individuals will focus on the area in which they think will gain the most, thereby reaping the biggest reward. In the case of a linear function of
rewards, the goals of enhancing learning and obtaining rewards are more closely intertwined than with the step function of rewards.

Fourth, in non-experimental settings individuals may not be so explicitly informed about strengths and weaknesses. The feedback of the current study might be an external validity problem because research has shown that individuals are not always aware of their own weaknesses (Kruger & Dunning, 1999; Dunning, Johnson, Ehrlinger, & Kruger, 2003). In particular, the same subset of knowledge, skills, and abilities is required for both the ability to perform and the ability to evaluate the performance. Therefore, when someone is a poor performer, it is unlikely that this person has the metacognitive awareness that he or she is mediocre at the task (Kruger & Dunning, 1999). That is to say, individuals who are incompetent do not evaluate their own thoughts and abilities accurately. Additionally, there is extensive research concerning individuals’ abilities to accurately assess how well and how much they are learning. Individuals are often ineffective at learning and cannot spot this ineffectiveness (Bjork et al., 2013). To address external validity, a possible future avenue of research may examine if the multiple-goal pursuit model predicts study topic choice if individuals are not told explicitly which areas are strengths or weaknesses. However, it is also important to note that many occupations do have performance management processes that give feedback about employees’ personal strengths and weaknesses (Aguinis, 2009).

Moreover, researchers recently discovered that when individuals are given feedback about weaknesses, they become defensive and question the accuracy of the feedback in addition to showing less interest in future improvement (Sheldon, Dunning, & Ames, 2014). Studies show that defensiveness is usually a result of negative feedback
The authors, among others (Aguinis, 2009), called for research examining how to minimize defensiveness and maximize desire to improve upon weaknesses in real-world settings. Researchers may want to investigate how giving feedback in the manner of the current study (i.e., giving feedback about a strength at the same time as feedback about a weakness) compares to other modes of delivering feedback with the goal of minimizing defensiveness. Unfortunately, these specific questions could not be investigated in the current study because the independent variable was not the type or specifics of the feedback provided.

**Practical Implications and Conclusion**

The results of this study begin to explore how individuals make learning decisions in the workplace. In applied settings, organizations pay high prices for formal education to direct employee learning (Reingold, 1997; Salas, Weaver, & Shuffler, 2012). However, individuals at work seem to engage in learning and development without formal intervention (Crant, 2000; Clardy, 2000; Frese, Garst, & Fay, 2007; Goldstein & Ford, 2002). The current study investigated how organizations might predict the choices employees make concerning self-directed learning at work.

To apply this research, organizations may want to focus on why individuals might engage in continuous, self-directed learning at work. That is, organizations should consider how individuals make decisions that might result in obtaining rewards and/or enhancing learning. In considering obtaining rewards, organizations should focus on tailoring their performance management systems to reinforce the right behaviors, which entails an analysis of the reward structure (Aguinis, 2009). If organizations desire employees to improve upon areas of weakness, the reward structure of the performance
management system should reward employees based on improvement in particularly weak areas. In considering enhancing learning, organizations might encourage beliefs in future expected learning. That is, organizations could promote either the belief in the Matthew effect or the belief in the asymptotic effect to encourage self-directed learning geared toward strengths or weaknesses respectively. By considering these goals, organizations may be able to increase motivation for self-directed learning. Moreover, the results of this study and future follow-up studies may increase the cost effectiveness of learning and development programs in organizations.

In conclusion, the current study demonstrates that individuals make learning choices according to expectancy theory and dynamic self-regulation theory. In particular, multiple goals drive individuals' choices in determining what to learn. Although there is much still to be understood about continuous, self-directed learning and making resource allocation decisions among multiple areas, the present study expands the field’s understanding of these critical behaviors. Overall, there are many directions for future research that could answer questions about anticipated relative improvement, learning goal orientation, other types of goals, other reward thresholds and structures, and the relevance of feedback. The current study is just beginning to explore the specifics of self-directed learning and decision making.
References


*Psychological Review, 84,* 191–215.


Appendix A: Additional Variables

This appendix describes the additional variables measured in this thesis and the results associated with relevant statistical tests involving the additional variables.

Affect

After the practice quizzes and the feedback, participants answered a series of questions about their current affect to determine if participants in the different conditions had different emotions. Participants rated emotions related to negative self-evaluation, positive feelings, and dissonance discomfort. The negative self-evaluation factor had an alpha of .88, the positive feelings factor had an alpha of .87, and the dissonance discomfort factor had an alpha of .81 (Matz & Wood, 2005).

An independent samples $t$-test was conducted to compare negative self-evaluation, positive feelings, and dissonance discomfort between the two role flexible conditions. There was no difference between individuals in the high role flexible condition ($M = 1.66, SD = .85$) and low role flexible condition ($M = 1.66, SD = .88$) in emotions related to negative self-evaluation, $t(169) = -.01, p = .992, d = 0$. There was no difference between individuals in the high role flexible condition ($M = 4.60, SD = 1.38$) and low role flexible condition ($M = 4.70, SD = 1.18$) in emotions related to positive feelings, $t(169) = -.53, p = .598, d = .078$. Lastly, there was no difference between individuals in the high role flexible condition ($M = 2.03, SD = 1.09$) and low role flexible condition ($M = 2.03, SD = 1.10$) in emotions related to dissonance discomfort, $t(169) = -.05, p = .959, d = 0$. 
**Anticipated Relative Improvement**

I included five extra sets of items to measure anticipated relative improvement. Belief in the asymptotic effect versus belief in the linear effect versus belief in the Matthew effect was computed in the same way as detailed in the Method section for these five sets of questions. For the first set of questions besides the set detailed in the Method section, participants indicated how much time (in minutes) they thought they needed to study to achieve 80% on either trivial pursuit topic. The second question was, “Which do you think will improve more in 20 minutes?” with three multiple choice options: “Science and Nature”, “Arts and Entertainment” or “Both will improve the same amount.” Third, participants answered: “How much do you believe it is easier to build knowledge about a topic you already have some knowledge of than to build knowledge about a topic you do not know much about initially?” and “How much do you believe it is easier to build knowledge about a topic you do not know much about initially than it is to accrue more knowledge about a topic you already have some knowledge of?” Participants answered these questions on 101-point scales (0 – I do not believe this at all to 100 – I believe this completely). Fourth, participants answered: “In a classroom, there is a range of ability. Who do you think will gain more knowledge during the course of a semester?” with three multiple choice options: “Those who are already knowledgeable about the subject,” “Those who do not know much about the subject initially,” and “All the students will likely gain the same amount of knowledge during the semester.” Fifth, participants answered: “Which of the above situations applies to the Trivial Pursuit task in this study?” “Easier to build knowledge about topic I already have some knowledge of”, “Easier to build knowledge about topic I do not know as much about initially,” and
“It is equally easy to build knowledge in both areas for me.” Cronbach’s alpha for the 6 anticipated relative improvement measures, including the one used in the current study analyses, was .334, indicating that the questions were not all assessing the same construct. Future research should investigate how to best measure this construct.

Besides the anticipated relative improvement item set used in the current study, no calculated anticipated relative improvement variable significantly predicted study topic choice. However, adding the continuous asymptotic belief variable, “How much do you believe it is easier to build knowledge about a topic you do not know much about initially than it is to accrue more knowledge about a topic you already have some knowledge of?” to the logistic regression with role flexibility and learning goal orientation did predict a significant amount of the variance in study topic choice as a set, $\Delta \chi^2 (3, N = 171) = 47.624$, $p < .001$, Nagelkerke $R^2 = .325$. The asymptotic belief variable also predicted study topic choice individually, $Wald \chi^2 (1, N = 171) = 4.67$, $p = .031$, $OR = 1.01$, in the presence of the other predictors. However, it is possible that individuals did not understand the wording or content of this question, as the scores on this continuous asymptotic effect belief question should have been negatively correlated with the scores on the continuous Matthew effect belief question. There was insufficient evidence to conclude that there was a significant negative linear relationship between scores on the continuous asymptotic effect belief question and the continuous Matthew effect belief question, $r = -.109$, $p = .155$.

In addition, there was a gender effect on the categorical anticipated relative improvement variable reported in the Results section of this thesis. When splitting the file by gender, role flexibility, anticipated relative improvement, and learning goal orientation
as a set predicted study topic choice for females, $\Delta \chi^2 (4, N = 109) = 37.02, p < .001$, Nagelkerke $R^2 = .384$ and males, $\Delta \chi^2 (4, N = 62) = 22.40, p < .001$, Nagelkerke $R^2 = .409$.

According to the logistic regression, when females believed in the asymptotic effect, the odds of choosing a weakness were 3.99 times higher than the odds of choosing a strength in the presence of the other predictors, $Wald \chi^2 (1, N = 109) = 5.72, p = .017$. None of the individual comparisons of beliefs for males were significant (all $p$'s > .05). The Holm (1979) procedure was used to control for family-wise Type I error rate. It is possible that there were not enough men in the sample to achieve the power to detect differences among the comparisons. Another possibility is that anticipated relative improvement is more salient or more important for women than men. This question should be investigated in future research. Descriptively, 22 men believed in the asymptotic effect; 3 men believed in the linear effect; 37 men believed in the Matthew effect. For women, 28 women believed in the asymptotic effect; 21 believed in the linear effect; 60 believed in the Matthew effect. The percentages of all individuals who fell into each belief (i.e., asymptotic effect, linear effect, Matthew effect) for each question, which describes the distributions of each belief for each question and the zero-order correlations of all six variables are on the following pages.
Table A1

*Distribution for “How much do you think you can improve your knowledge of Science and Nature (Arts and Entertainment) in 20 minutes?” (N = 171)*

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Anticipated Relative Improvement Belief</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asymptotic Effect</td>
<td>50</td>
<td>29.2</td>
</tr>
<tr>
<td>Linear Effect</td>
<td>24</td>
<td>14.0</td>
</tr>
<tr>
<td>Matthew Effect</td>
<td>97</td>
<td>56.7</td>
</tr>
</tbody>
</table>

Table A2

*Distribution for “How much time, in minutes, do you think you will need to study to achieve 80% on the final quiz in Science and Nature (Arts and Entertainment)?” (N = 169; two individuals gave nonsense answers)*

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Anticipated Relative Improvement Belief</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asymptotic Effect</td>
<td>19</td>
<td>11.1</td>
</tr>
<tr>
<td>Linear Effect</td>
<td>56</td>
<td>32.7</td>
</tr>
<tr>
<td>Matthew Effect</td>
<td>94</td>
<td>55.0</td>
</tr>
</tbody>
</table>

Table A3

*Distribution for “On which do you think you will improve more in 20 minutes?” (N = 171)*

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Anticipated Relative Improvement Belief</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asymptotic Effect</td>
<td>62</td>
<td>36.3</td>
</tr>
<tr>
<td>Linear Effect</td>
<td>39</td>
<td>22.8</td>
</tr>
<tr>
<td>Matthew Effect</td>
<td>70</td>
<td>40.9</td>
</tr>
</tbody>
</table>
Table A4
Distribution for “How much do you believe it is easier to build knowledge about a topic you already have some knowledge of than to build knowledge about a topic you do not know much about initially (easier to build knowledge about a topic you do not know much about initially than it is to accrue more knowledge about a topic you already have some knowledge of)?” (N = 171)

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Anticipated Relative Improvement Belief</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asymptotic Effect</td>
<td>24</td>
<td>14.0</td>
</tr>
<tr>
<td>Linear Effect</td>
<td>14</td>
<td>8.2</td>
</tr>
<tr>
<td>Matthew Effect</td>
<td>133</td>
<td>77.8</td>
</tr>
</tbody>
</table>

Table A5
Distribution for “In a classroom where there is a range of knowledge about a subject, who do you think will gain more knowledge during the course of a semester?” (N = 171)

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Anticipated Relative Improvement Belief</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asymptotic Effect</td>
<td>59</td>
<td>34.5</td>
</tr>
<tr>
<td>Linear Effect</td>
<td>18</td>
<td>10.5</td>
</tr>
<tr>
<td>Matthew Effect</td>
<td>94</td>
<td>55.0</td>
</tr>
</tbody>
</table>

Table A6
Distribution for “Which of the above situations applies to the Trivial Pursuit task in this study?” (N = 171)

<table>
<thead>
<tr>
<th>Variable</th>
<th>N</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Anticipated Relative Improvement Belief</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asymptotic Effect</td>
<td>30</td>
<td>17.5</td>
</tr>
<tr>
<td>Linear Effect</td>
<td>9</td>
<td>5.3</td>
</tr>
<tr>
<td>Matthew Effect</td>
<td>132</td>
<td>77.2</td>
</tr>
</tbody>
</table>
Table A7
Zero-Order Correlations for the Six Anticipated Relative Improvement Variables (N = 171)

<table>
<thead>
<tr>
<th>Variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Continuous Topic Question</td>
<td>-----</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Time Topic Question</td>
<td>.235</td>
<td>-----</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. Categorical Topic Question(^a)</td>
<td>.262**</td>
<td>.083</td>
<td>-----</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Matthew/Asymptotic Definition Question</td>
<td>.055</td>
<td>-.056</td>
<td>.153*</td>
<td>-----</td>
<td></td>
<td></td>
</tr>
<tr>
<td>5. Classroom Question(^b)</td>
<td>.139</td>
<td>-.093</td>
<td>.248**</td>
<td>.248**</td>
<td>-----</td>
<td></td>
</tr>
<tr>
<td>6. Applies to Study Question(^c)</td>
<td>.000</td>
<td>.044</td>
<td>.193*</td>
<td>.352**</td>
<td>.421**</td>
<td>-----</td>
</tr>
</tbody>
</table>

Note: Each listed question 1-6 corresponds to the Appendix Tables 1-6.
\(^a\)Categorical Topic Question was coded 1 = belief in asymptotic curve, 2 = belief in linear learning, 3 = belief in Matthew curve
\(^b\)Classroom question was coded 1 = belief in asymptotic curve, 2 = belief in linear learning, 3 = belief in Matthew curve
\(^c\)Applies to Study Question was coded 1 = belief in asymptotic curve, 2 = belief in linear learning, 3 = belief in Matthew curve
*p<.05. **p<.01.
Preference

Participants also answered how much they would prefer to study either topic in the process of indicating which topic they would like to choose to study for 20 minutes prior to the final trivial pursuit quiz. None of the predictors, nor any interactions, accounted for a significant amount of variance in the criterion variable (all $F$s < 1.5, all $t$s < 0, all $p$s > .19).

Valence

Participants answered three types of questions indicating the valence or value of choosing to study the different topics. The first question asked, “How important is it to you that you do well on the trivial pursuit quiz in Science and Nature (Arts and Entertainment)?” The second question asked, “How much do you value learning about Science and Nature (Arts and Entertainment)?” The third question asked, “How satisfied would you be if you improved your knowledge in Science and Nature (Arts and Entertainment)?” Participants answered these questions on 101-point slider scales (0 - not at all to 100 - very important/I value this completely/completely satisfied). Participants also answered a question about how much they valued potentially winning $5 on a scale from 0 to 100. In order to determine if the second and third valence questions were potentially better measures of learning goal orientation for the current study than the learning goal orientation scale, I averaged the responses on the second and third valence questions for both topics when the set was asked before the role flexibility manipulation and after the role flexibility manipulation. This alternative way of operationalizing learning goal orientation did not predict study topic choice in the presence of role flexibility and anticipated relative improvement, $Wald \chi^2(1, N = 171) = 3.06$, $p = .08$, OR
= 1.02, and in particular, did not interact with anticipated relative improvement (in a test of Hypothesis 4), \( \text{Wald } \chi^2(2, N = 171) = 1.14, p = .57 \) (omnibus test: \( \Delta \chi^2(4, N = 171) = 60.02, p < .001, \text{Nagelkerke } R^2 = .395 \)). There was a significant positive linear relationship between learning goal orientation and the valence average, \( r = .261, p = .001 \), which may explain why the alternative valence variables did not predict study topic choice.
Appendix B: Logistic Regression Based on Expectancy Response

The following results reflect running all analyses from the Results section using the 67.8% of participants who believed the feedback in responding to expectancy questions asking specifically about expectancy for their topic of strength according to the computer feedback versus expectancy for their topic of weakness according to the computer feedback. In running the analysis with only individuals who believed the feedback according to the above particular manipulation check, the model with the predictors was a better fitting model than the null model, $\Delta \chi^2 (4, N = 116) = 51.66, p < .001$, Nagelkerke $R^2 = .48$ (see Table B1).

Table B1
Summary of Hierarchical Logistic Regression Analysis for Predicting Study Topic Choice from the Predictors Based on Appendix B Manipulation Check

<table>
<thead>
<tr>
<th>Variable</th>
<th>$B^a$</th>
<th>$X^2_{Wald}$</th>
<th>$OR$</th>
<th>$\Delta X^2_{LR}$</th>
<th>$\Delta R^2_{Nagelkerke}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Role Flexibility$^b$</td>
<td>3.13</td>
<td>35.67**</td>
<td>22.72</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ARI$^c$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asymptotic Effect Belief</td>
<td>0.72</td>
<td>1.50</td>
<td>2.05</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LGO</td>
<td>-0.26</td>
<td>0.85</td>
<td>0.77</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Step 2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ARI X LGO</td>
<td></td>
<td></td>
<td></td>
<td>3.15</td>
<td>0.02</td>
</tr>
</tbody>
</table>

Note. $N = 116$. Strength was coded as “0” and weakness was coded as “1”. ARI = anticipated relative improvement. LGO = learning goal orientation. $^a$Estimated regression coefficients at entry. $^b$Role flexibility was coded as “0” = high role flexibility and “1” = low role flexibility. $^c$Anticipated relative improvement was dummy coded with Matthew effect belief as the reference level. *$p < .05$. **$p < .01$.

I also ran the analyses using participants’ perceptions about which topic was their strength and which topic was their weakness after the manipulated feedback, instead of using 67.8% of participants in the analyses. Results did not significantly differ from the analysis run with only the 67.8% individuals who believed the feedback.
Hypothesis 1 stated that high role flexibility would positively relate to choosing a strength. When including only the individuals who believed the feedback, high role flexibility increased the odds an individual would choose to study a strength over a weakness by 22.85 times over low role flexibility in the presence of the other predictors, $Wald \chi^2(1, N = 116) = 35.67, p < .001$ (see Table B1). These results strongly support Hypothesis 1.

Hypothesis 2 stated that low role flexibility would positively relate to choosing a weakness. Running the analysis with only the individuals who believed the feedback, low role flexibility increased the odds of individuals choosing to study a weakness over a strength by 22.72 times in the presence of the other predictors, $Wald \chi^2(1, N = 116) = 35.67, p < .001$ (see Table B1). These results strongly support Hypothesis 2.

Hypothesis 3 stated that belief in a Matthew effect would positively relate to choosing to study a strength and that belief in an asymptotic effect would positively relate to choosing to study a weakness. Anticipated relative improvement was tested as both a categorical and a continuous variable. As a categorical variable, the omnibus test for anticipated relative improvement was not significant in the presence of the other predictors, $Wald \chi^2(2, N = 116) = 2.15, p = .342$ (see Table B1). Likewise, when the analysis was run using anticipated relative improvement as a continuous variable, anticipated relative improvement did not significantly predict study topic choice.

Hypothesis 4 predicted an interaction between anticipated relative improvement and learning goal orientation ($M = 5.31, SD = .87$). Running the analysis with only the individuals who believed the feedback, the interaction between anticipated relative improvement...
improvement and learning goal orientation did not predict study topic choice, $Wald \chi^2(2, N = 116) = 3.04, p = .219$ (see Table B1). The results do not support Hypothesis 4.
Appendix C: Logistic Regression Based on Choice Response

The following results reflect running all analyses using the 89.5% of participants who indicated they believed the computer-generated manipulated feedback in responding to the question “Did you choose to study the topic that was your relative strength or your relative weakness?” In running the analysis with only individuals who believed the feedback according to the above particular manipulation check, the model with the predictors was a better fitting model than the null model, $\Delta \chi^2 (4, N = 153) = 60.03, p < .001$, Nagelkerke $R^2 = .43$ (see Table C1).

Table C1
Summary of Hierarchical Logistic Regression Analysis for Predicting Study Topic Choice from the Predictors Based on Appendix C Manipulation Check

<table>
<thead>
<tr>
<th>Variable</th>
<th>$B^a$</th>
<th>$X^2_{Wald}$</th>
<th>OR</th>
<th>$\Delta X^2_{LR}$</th>
<th>$\Delta R^2_{Nagelkerke}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>Step 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Role Flexibility$^b$</td>
<td>2.74</td>
<td>37.80**</td>
<td>15.38</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ARI$^c$</td>
<td></td>
<td>12.10**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Asymptotic Effect Belief</td>
<td>0.96</td>
<td>4.02*</td>
<td>2.62</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LGO</td>
<td>-0.10</td>
<td>0.20</td>
<td>0.90</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Step 2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ARI X LGO</td>
<td>-</td>
<td>2.18</td>
<td>0.02</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note. $N = 153$. Strength was coded as “0” and weakness was coded as “1”.
ARI = anticipated relative improvement.
LGO = learning goal orientation.
$^a$Estimated regression coefficients at entry.
$^b$Role flexibility was coded as “0” = high role flexibility and “1” = low role flexibility.
$^c$Anticipated relative improvement was dummy coded with Matthew effect belief as the reference level.
*p < .05. **p < .01.

Hypothesis 1 stated that high role flexibility would positively relate to choosing a strength. When including only the individuals who believed the feedback of the above
manipulation check, high role flexibility increased the odds an individual would choose to study a strength over a weakness by 15.45 times over low role flexibility in the presence of the other predictors, $Wald \chi^2(1, N = 153) = 37.80$, $p < .001$ (see Table C1). These results strongly support Hypothesis 1.

Hypothesis 2 stated that low role flexibility would positively relate to choosing a weakness. Running the analysis with only the individuals who believed the feedback, low role flexibility increased the odds of individuals choosing to study a weakness over a strength by 15.38 times in the presence of the other predictors, $Wald \chi^2(1, N = 153) = 37.80$, $p < .001$ (see Table C1). These results strongly support Hypothesis 2.

Hypothesis 3 stated that belief in a Matthew effect would positively relate to choosing to study a strength and that belief in an asymptotic effect would positively relate to choosing to study a weakness. Anticipated relative improvement was tested as both a categorical and a continuous variable. As a categorical variable, running the analysis with the individuals who believed the feedback according to the above manipulation check, anticipated relative improvement related to study topic choice in the presence of the other predictors, $Wald \chi^2(2, N = 153) = 12.10$, $p < .001$ (see Table C1). I also made pairwise comparisons using the Holm (1979) procedure to control for family-wise Type I error rate. If individuals believed in the linear effect, the odds of choosing to study a strength were 4.95 times greater than if individuals believed in the Matthew effect, $Wald \chi^2(1, N = 153) = 6.12$, $p = .013$. Additionally, if individuals believed in the linear effect, the odds of choosing to study a strength were 12.99 times greater than if individuals believed in the asymptotic effect, $Wald \chi^2(1, N = 153) = 12.01$, $p = .001$. Lastly, if individuals believed in the asymptotic effect, the odds of choosing to study a weakness were 2.62 times
greater than if individuals believed in the Matthew effect, $Wald \chi^2(1, N = 153) = 4.02, p = .045$ (see Table C1). When the analysis was run using anticipated relative improvement as a continuous variable, anticipated relative improvement did not significantly predict study topic choice. These results partially support Hypothesis 3.

Hypothesis 4 predicted an interaction between anticipated relative improvement and learning goal orientation ($M = 5.30, SD = .87$). The interaction between anticipated relative improvement and learning goal orientation did not predict study topic choice, $Wald \chi^2(2, N = 153) = 2.07, p = .355$ (see Table C1). The results do not support Hypothesis 4.