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Change one can believe in: Adding learning to computational models of self-regulation

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ABSTRACT

Theories of self-regulation describe motivation as a dynamic process of goal choice and goal striving. To facilitate those processes, individuals learn about themselves and their environment, which is an internal dynamic process. However, the precise nature of the relationship between these learning and motivational processes is not well specified. This article integrates formal models of learning, goal choice, and goal striving using a single information processing structure found in self-regulatory models of motivation. Results from two published studies (DeShon & Rench, 2009; Schmidt & DeShon, 2007) validate the model. In both cases, the integrated model accounts for findings that previous theories of self-regulation could not explain. Discussion focuses on additional tests to validate the model and on the value of incorporating formal models from the cognitive, learning, and motivational literatures to account for behavior in complex settings and over time.

Introduction

Behavior is inherently complex and dynamic (Atkinson & Birch, 1970). One reason for this complexity is that organisms act to seek or maintain numerous goals based on changing internal and external conditions (Austin & Vancouver, 1996). Humans can also think about the possible consequences – good and bad – of their actions and the likelihood those consequences will materialize using their understanding of the environment and themselves (Krantz & Kunreuther, 2007). These capacities, their operation (i.e., their dynamics), and their development are especially important when considering motivation and behavior in work settings (Kanfer, 2012; Mitchell & James, 2001). Perhaps not surprisingly, developing a firm understanding of the mechanisms involved in these processes is a challenge. Moreover, several scholars are concerned that path models describing the relationships among variables and the verbal explanations accompanying these models are insufficient for explicating and communicating theories of human behavior (Busemeyer & Diederich, 2010; DeShon, 2012; Farrell & Lewandowsky, 2010; Sun, 2008; Vancouver, 2012). To address this concern, these scholars suggest using formal theories because they can provide a more precise, transparent, and internally consistent approach to theorizing. In particular, computational models of subsystem processes are a particularly appropriate type of formal theorizing because they can be simulated and provide predictions of behavior over time (Adner, Polos, Ryall, & Sorenson, 2006).

Toward that end, Vancouver, Weinhardt, and Schmidt (2010) recently presented a computational model of multiple-goal pursuit that describes processes for thinking and acting over time. In this model, they integrated theories of goal choice and goal striving, which tend to be considered in separate, middle-range theories (Klein, Austin, & Cooper, 2008). Moreover, the model was dynamic, predicting how individuals respond to changes in the environment brought on by their own actions as well as outside forces. The multiple-goal pursuit model (MGPM; Vancouver et al., 2010) represents an instantiation of a larger formal theory of self-regulation presented by Vancouver (2008). That theory, which borrows heavily from control theory perspectives of human behavior (e.g., Carver & Scheier, 1998; DeShon & Gillespie, 2005; Ford, 1992; Lord & Levy, 1994; Powers, 1978), describes mechanisms alleged to represent action, thinking, feeling, and learning processes. One of the more remarkable elements of the theory is that the basic mechanism for all these processes is the same. Specifically, at the core of control theory is a weighted difference function driving a negative feedback loop that arcs through the environment. This weighted difference function represents a self-regulatory agent, which is a very simple subsystem of the human system (Vancouver, 2005). Via this conceptualization, the complexity of human behavior arises from a combination of environmental dynamics and, more importantly, the organization of multiple agents within individuals.

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At this time, much scholarly work is needed to conceptualize and verify the specific nature and organizations of agents that might account for the variety of phenomena representing human behavior. By developing a working simulation of goal choice and goal striving, the MGPM represents an example of that kind of scholarly work. However, that model was limited to the dynamics of the environment and information (i.e., signals) flowing through the individual. It did not address dynamic processes that might occur within the individual (e.g., processes that change what or how individuals process signals). Such mechanisms would lead to the relatively permanent change in individuals commonly referred to as learning (Weiss, 1990).

Although applied psychologists often consider learning the province of training and development, learning theories have also long been of central interest to organizational behavior and motivation researchers (Pinder, 2008). Indeed, learning is an important process in human functioning that supports goal striving, goal choice, and other self-regulatory processes (Sitzmann & Ely, 2011). For instance, expectancy and social cognition theories (e.g., Bandura, 1986; Porter & Lawler, 1968; Vroom, 1964) assume much of the variance in motivation is based on learned beliefs about environmental contingencies, properties of the self (e.g., beliefs about capacity), and experience with outcomes. However, the bulk of the research on learning within organizational science does not address the sub-system processes that lead to learning, focusing instead on a higher-level analysis. For example, research has shown that error management training increases learning (Keith & Frese, 2005). Yet, as Keith and Frese note, the specific processes on which error management training capitalizes are less well known. Here we offer an account of the subsystem processes that lead to learning and intra-individual change.

Of course, formal models of learning mechanisms are common in cognitive psychology (Young & Wasserman, 2005) and some have appeared in organization science (Gibson, Fichman, & Plaut, 1997; March, 1996). We incorporate some of that knowledge here. Integrating these mechanisms with modern conceptualizations of goal choice and goal striving provide a more comprehensive theory of motivation and self-regulation. Specifically, we want to explain how an individual develops understandings of themselves and the environment that are useful for self-regulation. For example, individuals might create beliefs of the effectiveness of actions (i.e., expectancies; self-efficacy) or future conditions, like when professors learn to anticipate the kinds of questions they might receive on a set of material presented to a class or the reviews they might get on a journal article and use those anticipated events to adjust their presentations or articles. A better understanding and integration of these dynamic processes is likely to facilitate the development of interventions targeted at improving self-regulation (Boekaerts, Maes, & Karoly, 2005; Vancouver & Day, 2005). Moreover, if the learning subsystem is consistent with the goal-choice and goal-striving subsystems, then the representation of self-regulation will be conceptually parsimonious as well comprehensive (Vancouver, 2008).

Toward these ends, the goals of the current project are fourfold. First, we seek to add understanding of individual change to the MGPM, which at this time only includes behavior and environment change. Second, we use that understanding to account for how individuals might handle uncertainty in the environment as well as learn helpful information about oneself that might be useful for planning and making decisions. Third, we seek to maintain parsimony by using the same core concept (i.e., the self-regulatory agent) used in the MGPM. Finally, we accomplish the above formally by using a computational representation of self-regulation. In the following sections, we review the core concept in our approach and how it is used in the MGPM. We then review learning concepts and some formal modeling concepts found in the cognitive literature. Next, we explain how learning might support multiple goal pursuit, incorporating the learning agents into the MGPM. Finally, we assess the validity of the resulting model by assessing its ability to account for the phenomena it purports to explain.

A computational theory of self-regulation

In recent years, there has emerged an increasing desire to develop a comprehensive, integrative theory of human work motivation and behavior (Locke & Latham, 2004; Pinder, 2008; Steel & König, 2006). Toward that end, self-regulation theories have shown promise (Diefendorff & Chandler, 2011; Lord, Diefendorff, Schmidt, & Hall, 2010). Self-regulation theories highlight the agentic, goal-directed, quality of behavior (Bandura, 1997; Vancouver & Day, 2005). A central construct in self-regulation theories are goals, which are internally represented desired states (Austin & Vancouver, 1996), and a central process in these theories is discrepancy reduction (Vancouver, 2005).[1] In particular, the individual maintains or achieves goals by perceiving the states of variables and acting on discrepancies between the perceived states and the desired states (i.e., goal). The actions affect the states of interest, moving them toward the goals and thereby reducing the discrepancies. Because the actions partially determine the states of the variables and perceived states partially determine the actions, the process reflects a feedback loop. Moreover, because discrepancies signal actions that reduce the discrepancies, the sign of the loop is negative. When operating properly, a negative feedback loop keeps "regular" or "controls" the variable's perceived state much like a cruise control system in a car keeps regular or controls the speed of the car as perceived by the car's speedometer (Vancouver & Day, 2005). It is this process that accounts for the self-regulation or control theory labels often used interchangeably in the literature (e.g., Carver & Scheier, 1981, 1998).[2]

Fig. 1 represents the basic negative feedback, or discrepancy-reducing, loop. The figure makes explicit the key functions needed for self-regulation. Specifically, the input function translates signals external to the system (i.e., inputs) into a single signal used by the system. Typically, this involves translating stimuli (s) indicating the state of some variable (v) into a perception (p) of that state. The perception is then available to other functions in the system. Mathematically, we represent the input function as a product of two vectors: a vector of inputs and a vector of weights for the inputs. Multiplying the two vectors gives a scalar (i.e., single) value much like a regression equation gives a single prediction based on a set of weighted inputs. Typically, in self-regulation models, the inputs are actually the outputs from other functions or nodes (Powers, 1973). We should also note that connectionist (i.e., neural network) models describe a similar arrangement, except that the input function is called a node or processing unit (Gibson et al., 1997). Given that the outputs from input functions are labeled perceptions (p) in self-regulation models, Vancouver (2008) represented the input function as follows:

$$p = \mathbf{w}_s \mathbf{p}_s, \tag{1}$$

[1] Another central process in self-regulation theories is discrepancy production via the adoption of goals that are beyond current conditions. Some suggest that discrepancy production is a byproduct of discrepancy reduction (e.g., Scherbaum & Vancouver, 2010); whereas, others suggest that discrepancy reduction is dependent on the discrepancy production, making discrepancy production more interesting (Bandura, 1997). In this paper, we merely assume discrepancies exist. We do not address the possible processes that produce them.

[2] The loop can also represent the motivation for one-time achievements, like obtaining a Ph.D., where the regularity element is less obvious and control seems to qualify the actions as opposed to the perceptions. This achievement type of context appears to have created some semantic confusion (Vancouver, 2000; Vancouver & Scherbaum, 2008).