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Motivational Constructs: Implications for Instruction and Learning

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Abstract This paper, then, has three purposes. First, the paper will identify relevant constructs from the motivational literature that may usefully aid in the development of a theory of motivational load. Second, the paper explores how previously validated indexes of motivation, active choice, mental effort, and persistence, may inform dynamic measurement and support of motivation during learning. Last, the paper proposes a substantive dialogue focused on theory building and the development of research questions. The literature examining motivation in learning environments provides important insights into human behavior; allowing prediction of goal-related behaviors that relate to achievement. This body of literature has, until quite recently, been notable for the degree to which lines of research were pursued with little attention to an overarching theoretical framework.
Keywords: motivational constructs motivation, learning, instruction

Introduction

Recently, researchers and instructional design theorists have turned their attention to applying theoretical structures from Cognitive Load Theory (CLT) to what has been called *motivational efficiency* (Paas, Tuovinen, van Merriënboer, & Darabi, 2005). This is an important development in instructional design because multiple lines of research from the field of motivational effects on goal-oriented performance can be brought to bear on questions of motivational efficiency in instructional design. The call for an integrative approach to the role of motivation in training and instruction was made effectively by Colquitt, LePine and Noe (2000) in their exhaustive review of twenty years of literature on training outcomes. Motivational variables explain training outcomes over and above cognitive abilities (Colquitt, LePine and Noe, p. 702) and, due to their inherent responsiveness to manipulation (Pintrich and Schunk, 2002) provide a valuable point of focus for instructional designers who seek to improve learning. This claim is hardly controversial – there is wide agreement about the importance of motivation in learning (Salomon, 1984; Ford, 1992; Pintrich and Shunk, 2002). The difficulty has been in the ways in which motivation has been defined and measured, and achieving synthesis across findings. By focusing on self-efficacy, or goal orientations or emotions, or any one of a number of other meaningful sources of outcome variability, one may clearly see the trees, but fail to appreciate the forest in which they grow.

The importance of motivation in learning

Self-Efficacy

If learner ability is the engine that drives learning, then motivation can be thought of as the fuel for the engine. Regardless of the size or quality of the engine, without fuel, the engine (or in this case, the learner) is going nowhere. The literature on motivation, particularly since the mid-1970's, has identified several layers of interacting constructs that affect an individual's motivation to learn, or what is more typically referred to as goal-specific motivation (Pintrich and Schunk, 2002). Self-efficacy (Bandura, 1997) is a vital construct to consider when building a theory of motivational load. Self-efficacy can be thought of as, "personal judgments of one's capabilities to organize and execute courses of action to attain designated goals" (Zimmerman, 2000, p. 83). As is often the case when examining issues of motivation, self-efficacy is a continuous variable (e.g. from 0 to 100%), which changes over time as learning tasks and learner prior knowledge change. While self-efficacy may be conceptualized as a relatively stable learner characteristic, it may be more useful to think of self-efficacy in Bandura's (1977) terms as varying with tasks and learner prior knowledge of tasks. Patterns in goal selection and pursuit relate to self-efficacy. Because self-efficacy varies with tasks and prior knowledge, (among other variables), it can help us predict who will and will not be motivated to learn a specific task (Bong and Clark, 1999). Valid and reliable scales for task-specific self-efficacy can be developed, following guidelines set forth by Bandura (1997). These scales can then be incorporated into an assessment of learner characteristics to which an instructional design can dynamically respond – providing additional supportive feedback for individuals with relatively low self-efficacy (e.g. focusing on correct implementation of procedures or strategies for responses) and reducing the amount of feedback for individuals who are found to have relatively high self-efficacy (Song and Keller, 2001).

Goal Orientation

Dweck and Leggett (1988) have described how learners can also be understood to exhibit *goal orientations* that broadly govern the ways in which they pursue goals. Four specific orientations described by Dweck and Leggett interact to influence goal pursuit: *performance, mastery, approach,* and *avoidance*. If one pictures a two-by-two frame of cells, individuals can be located in any of four cells – performance approach, performance avoidance, mastery approach, and (in very rare cases) mastery avoidance.

Table 1. Performance approach, performance avoidance, mastery approach, and mastery avoidance

	Approach	Avoidance
Mastery	Mastery-Approach	Mastery-Avoidance
Performance	Performance-Approach	Performance-Avoidance

The terms approach and avoidance are self-explanatory, but performance and mastery are of special relevance to this discussion, as they may influence the types of motivational support strategies likely to be effective for individual learners. Performance orientations are held by individuals who pursue goals in order to receive some external validation by attaining the goal at a specific level of proficiency. Performance-approach individuals actively pursue goals to do so, while performance-avoidance individuals actively retreat from goal pursuit in order to avoid the lack of validation they predict will follow a failed attempt (which in turn they assume will occur, based on low goal-specific self-efficacy). Mastery orientation, on the other hand, is one in which the individual pursues goals based on an internal desire to achieve the goal, regardless of perceived social rewards. Mastery orientation is most commonly observed paired with the approach pattern, although there may be individuals who avoid tasks for reasons relating to lack of desire to achieve the goal.

A number of independent studies have reported a positive relationship between m-a scores and the tendency to choose novel and challenging learning tasks (Ames, 1992; Elliott and Dweck, 1988). Pintrich and colleagues have established a similarly strong relationship between mastery-approach orientations and the investment of effort in novel and challenging learning tasks (Pintrich, 1993; Pintrich and DeGroot, 1990; Pintrich and Garcia, 1991; Pintrich, Smith, Garcia and McKeachie, 1993). In the case of goal orientations, the inverse of these relationships also holds. When students maintain a performance goal orientation, they are less likely to choose novel and challenging learning tasks (Nicholls, 1984), and less likely to invest sufficient mental effort to accomplish learning tasks. Thus when goal orientation scores are known it is possible to adjust instruction to provide maximum support for motivation.

Indexes of Motivation

Self-efficacy and goal orientation are vital constructs for theory building and understanding the ways in which motivation affects learning outcomes. However, the constructs are nevertheless problematic. Self-efficacy and goal orientation are typically measured using self-report techniques - which are not uniformly reliable across dynamic learning contexts (Gimino, 2000) Because dynamic, complex learning environments may present tasks deep in the lesson that are significantly more challenging than anticipated, pre-task assessments of efficacy may become less accurate or unstable as the lesson progresses. Similarly, goal orientations are not immutable, and may be inconsistently predictive of an individual's likelihood to pursue a goal. Pintrich and Schunk (2002) and others (Clark et al., 2006; Kanfer and Ackerman, 1989; Song and Keller, 2001) have suggested that there are relevant indexes of motivation that usefully inform the study of learner motivation: c*hoice*, *mental effort*, and *persistence*. Although they refer to them in terms of attentional effort, Kanfer and Ackerman (1989) focus on the core roles played by motivation in learning. Motivation, the fuel that drives the engine of learning, acts as a mediator of learning through mechanisms of resources allocation. While Kanfer and Ackerman describe these resources in terms of attention, which makes motivational constructs mesh neatly with constructs of self-regulation, the current trend is to describe motivation processes in terms of their effects on learning via the three indexes mentioned above.

<u>Choice</u> is the behavior of selecting and actively beginning to pursue a new goal. In many educational and work-training contexts choice, also known as goal-selection lies in the hands of the teacher or supervisor rather than within the individual. Zimmerman, Bandura, and Martinez-Pons (1992) found significant effect sizes (Cohen's d >1.2, p<.001) on scholastic achievement when goal selection was autonomous. This effect was not significant when goals were selected by others. This finding may be confounded by the likelihood of students with mastery-approach orientations to perform at higher levels than others, but should in any case inform the design of instructional media so that choice is embedded whenever possible. As defined by Salomon, <u>mental effort</u> is, "the number of non-automatic elaborations necessary to learn or solve a problem" (Salomon, 1984, p. 648). Mental effort has been measured in a number of ways (described below) but in all cases relates to cognitive resource allocation. <u>Persistence</u> is the behavior of engaging in the tasks required for goal achievement over some interval of time while avoiding distractions. These indexes, when treated as dependent variables, can serve as legitimate outcomes for a wide variety of independent variables related to motivation. For example, one might examine the effects of self-efficacy, goal orientation, locus of control, attributional attitudes, etc., on choice, mental effort, or persistence (Clark, 1999).

Issues in Measurement of Motivational Indexes

Measurement of choice

Measuring learner choice to pursue a new goal is straightforward – the learner selects a goal and begins, or does not select and begin. As mentioned above, the learner or trainee does not always have choice in task selection. This lack of choice may present motivational problems, particularly for tasks for which the learner has low efficacy, and in contexts in which the learner maintains a performance goal orientation.

Measurement of persistence

Measurement of persistence presents significant challenges. It may seem as though measuring persistence is no more complex than measuring the length of time a person spends in pursuit of a goal, and surely this is an important component of the measure. That said, such a direct measure may, in cases of performance delays or task abandonment, confound lack of persistence with intrusive, or 'ironic' mental processes, as described by Wegner (1997). When task complexity is very high, or when working memory is otherwise overburdened an unconscious monitor may intervene and distract the individual from their goal in order to preserve (Clark, 1999). In this way, what may appear to be a lack of motivation to persist should be seen as a predictable effect of excessive cognitive load. Although the learner may experience the effects of this ironic process differently from those who lack intention to persist, it is conceivable that an ironic mental process creates the sensation of decreased interest or task commitment.

The problem with measuring persistence is this: because the processes that allocate resources operate, in most cases, automatically, the learner may not be able to discern cases in which they consciously "choose" to disengage from goal pursuit from those cases in which an unconscious process chooses for them. It is plausible that such an unconscious mental process operates when working memory resources are overburdened, and that they are associated with ironic processes, as described by Wegner (1997) that create a sense of conscious choice when none exists. Because of the difficulties associated with measuring persistence *per se*, it may be most expedient to focus our attention on improved accuracy in measuring mental effort.

Measurement of mental effort

As with the measurement of persistence, measuring mental effort presents significant obstacles. While multiple measures of mental effort have been conceived – self-report, dual-task measures, and task engagement to name three of the more common methods (Paas and van Merriënboer, 1994; Salomon, 1984; Gimino, 2004; Flad, 2004), all seem to suffer from problems related to a lack of a linear relationship between perceived (and therefore, reported) mental effort and true levels of mental effort as task difficulty increases (due to sources of exogenous cognitive load such as increased complexity) (Gimino, 2002, Clark, 1999). The hypothesized linear relationship between task difficulty and investment of mental effort was revealed by Gimino (2004) to be curvilinear in nature. Individuals report ever increasing investment of mental effort as task difficulty increases, but in fact invest less and less mental effort after a critical (individual-specific) level of effort is reached. While this points to the problematic nature of previous work on mental effort, Gimino's finding is consistent with current understandings of cognitive architecture (Anderson and Libiere, 1998). Gimino's work also highlights the need for measures of mental effort with improved validity. She found that across 7 arithmetic problem sets of increasing complexity, there was no significant correlation between cognitive workload and mental effort (p. 143). There are multiple rival explanations for this finding – the tasks could have been highly automated for all participants, response times may have been an invalid measure of workload, or the self-report measure of mental effort may have been inaccurate.

Physiological measures of mental effort

A number of physiological measures of mental effort have been proposed. Among the most promising are measures of change in pupil size (Iqbal, Zheng, and Bailey, 2004) and peripheral vasoconstriction (Iani, Gopher, and Lavie, 2004). Iqbal, Zheng and Bailey found, using an eye-tracker, that pupil size changes correlated significantly with cognitive load for computer-based interactive tasks, and that these correlation reflected the dynamic nature of task difficulty and mental effort investment across task duration. A less intrusive measure of mental effort was described by Iani, Gopher, and Lavie, who found that constriction of the blood vessels in the fingers, as a reflection of sympathetic nervous system activation, can serve as a reliable measure of mental effort expenditure (p. 796). As with pupillary response, the measure of vasoconstriction was sensitive to differing task types, effects of exposure, and individual decrements in task performance. These studies represent demonstrations of objective measures of mental effort and as such, may usefully inform models of instructional design that seek to address mental effort dynamically. Unfortunately, as with previous physiological measures of mental effort, they are relatively intrusive and may be difficult to implement in applied settings.

Measurement of motivation in dynamic learning environments

Mental effort and performance gains

Recently developed models that seek to relate mental effort and performance (see, for example Paas et al, 2005) are most welcome. They should, however, respond directly to the complexity of measuring multiple motivational indexes in dynamic learning environments. By addressing the complexity of the relationships between mental effort and other indexes of motivation that are simultaneously active, one may model a more robust conceptualization of motivational efficiency. Resolving these issues requires a comprehensive approach to thinking about motivational load, one that attempts to account for variability in selecting goals and initiating goal pursuit, investing sufficient mental effort, and persisting until goals have been achieved.

Accurate measurement of the indexes of motivation in dynamic learning environments is important because without such assessment, appropriate modification of motivational supports (such as those described by Song and Keller, 2001, Keller and Suzuki, 2004) cannot occur. In fact, current models of motivationally adaptive software suggest strategies that may improve performance because of working memory (Cowan, 2001) or cognitive load (Van Merriënboer and Sweller, 2005) issues, as in the example of the measurement of task persistence described above. For example, as strategies for maintaining motivation, Song and Keller suggest using short segments of instruction, providing visual representations of concepts when possible, avoiding distracting visual elements, and matching task requirements to learner ability and experience levels. One would expect, based on nothing more than CLT that these strategies would lead to improved performance, which may in turn positively correlate with motivation. The issue at hand is whether or not these strategies relate directly to the assessment of learner starting, persisting, and mental effort. It will continue to be challenging to assess motivational efficiency as a construct until models examine the effects of motivational support strategies on validated indexes of motivation rather than focusing only on performance gains.

Of greater interest for the purposes of building a model of motivational load may be the ways in which Keller and Suzuki outline the steps for embedding motivational supports into instructional designs. This model begins, rightly, with a thorough assessment of learner skills levels and attitudes and proceeds with the development of a motivational profile for the learner before proceeding to support/strategy selection and placement. Keller and Suzuki's model may provide a template onto which theories of motivational load can be applied for purposes of research and/or design. In all cases, clarity and utility of findings will be strongly related to the degree with which the model allows measurement of the effects of experimental conditions on the indexes of motivation.

Motivational load

As is the case with cognitive load, it may be useful to separate out factors that affect learner motivation into distinct groups – the variables or values of variables that increase learner motivation, and the variables or values that decrease or fail to influence learner motivation. Custers and Aarts (2005) have identified positive affect (via "dopaminergic effects in cortical pleasure centers", p. 131) as an example of a variable value that increased future goal pursuit via choice. The memory of the pleasurable sensation associated with prior goal pursuit may, over time, become automated and lead to active choice for novel goals. As described above, excess burden on working memory may serve as an example of a variable value that decreases goal pursuit by decreasing effort or persistence through ironic mental processes. The figure below models the ways in which these groups of factors or values may affect motivation.

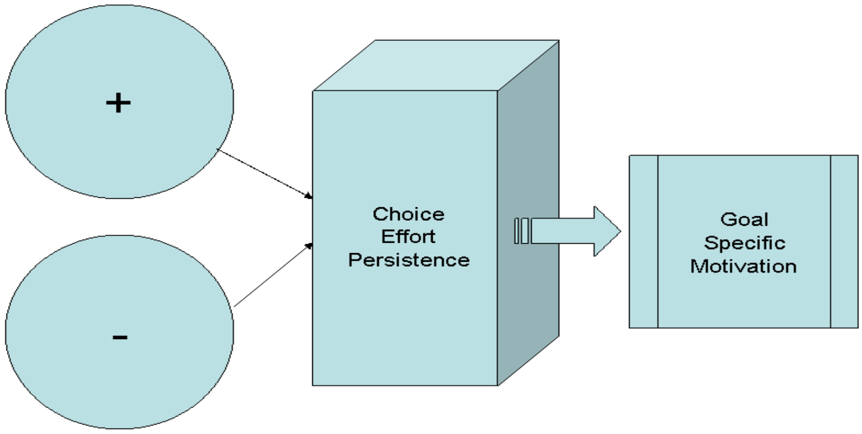

Figure 1. Groups of factors / values affect motivation

By focusing on the three indexes of motivation as the dependent variables in the model, a wide variety of independent variables could be tested for their effects on the indexes. For example, self-efficacy could operate as either a positive or a negative factor. Low task-specific self efficacy might lead to choosing not to begin a task, to applying insufficient effort, or to failing to persist. Conversely, higher levels of task-specific self efficacy might lead to positive expressions of choice, effort, and persistence. Likewise, goal orientations can be located within the model. Performance-approach and mastery-approach orientations exert positive effects on one or more of the motivational indexes, while performance-avoidance and mastery-avoidance exert negative effects on the indexes. Other motivational constructs, such as those proposed by Keller (ARCS model, 1987), Ford (1992), Kawada, Oettingen, Gollwitzer and Bargh (i.e., implicit goal projection, 2004), and Bandura (1997), might also be reasonably described as falling into one of the two groups of factors affecting motivational indexes.

Support for the relevance of the model

As mentioned in the introduction, the literature on motivational effects on learning has taken a splintered approach. In pursuit of parsimony or clarity of description, many authors address one piece of the motivational puzzle at a time. Few researchers have attempted to collect data in a manner that would allow for robust support for an integrated model of motivational load that relies on the indexes at hand.

Flad (2002), for example, found support for the predicted positive relationship between task difficulty and mental effort (Pearson's $r=.979$, $p<.05$, p. 75). This finding is predicted by CLT, and is consistent with prior results (Paas and van Merriënboer, 1993; Paas et al., 2003, 2005). In the model of motivational load described above, task difficulty acts as a predictor variable for mental effort, which in turn provides a context for understanding various motivation levels. Flad also found a significant, negative, linear relationship between self-efficacy and mental effort (Pearson's $r=.965$, $p<.01$). In this case, the learner's task-specific self-efficacy serves as a predictor variable, with decrements in self-efficacy noted with increases in task difficulty and expenditure of mental effort. This finding is consistent with Bandura's (1977) description of self-efficacy, in which prior experience serves as the basis for future estimates of efficacy, which in turn have been shown to affect mental effort investment (Clark, 1999) When one considers these results in light of the significant negative relationship Flad identified between task difficulty and performance, the complexity of the relationships between task difficulty, self-efficacy, mental effort, and performance becomes apparent. This complexity requires a parsimonious model for the calculation of motivation, a necessary first step in the development of a testable theory of motivational load for incorporation into instructional designs. The formula offered by Paas and colleagues (Paas and van Merriënboer, 1993; Paas et al., 2003, 2005) currently includes standardized scores for performance and effort, which are summed and divided by the root of two to obtain a measure of motivation. This formula might be made even more predictive of motivational levels if it included a standardized measure of persistence. Given the difficulties inherent in measuring persistence, the formula is a necessary step in the right direction.

Motivational Load in Adaptive Instruction

The remaining issue to be addressed is that of motivational load in adaptive instruction. Using the Paas et al.'s (2003, 2005) formula for motivation helps us to understand, after the task has been performed, the level of motivation demonstrated by the learner. The need for a measure of motivational load is, in some ways, the complement of observed levels of motivation. The difference is similar to that between the cognitive load inherent in a task and the observed cognitive workload(s) demonstrated by learners during instruction. Flad's (2002) study, the results of which were briefly described above, confirmed many of the predicted relationships between input variables such as task difficulty and indexes of motivation such as mental effort. A theory of motivational load extends and abstracts these relationships by asking the following question for learning task/leaner pairings: What is the level of motivation required for this learner to successfully complete this task? This question bears a bit of unpacking. The question requires knowledge of important sources of variability in motivation such as task-specific self-efficacy and goal orientations as well as the learner's general ability level (Snow et al., 1996) and the levels of extraneous and germane cognitive load for the task. When the relevant levels are known, current models of instructional design such as the 4C:ID model (van Merriënboer, 1997) could be adapted to include just-in-time motivational supports as well as just-in-time information supports for learning. For example, a very novel and challenging task assigned to a learner with average ability, a performance goal orientation and relatively low self-efficacy would carry a very high motivational load – meaning that the level of motivation necessary to produce sufficient allocation of attentional and other cognitive resources would be great. In contrast, for the same difficult task, a learner with average ability, a mastery orientation and strong self-efficacy the motivational load would be relatively low – meaning that the necessary motivation for task completion pre-exists in the learner and does not need to be explicitly supported. It is important to note that motivational load is a context-dependent construct. Unlike cognitive load, there is no fixed level of motivation necessary for task completion that resides solely within the task. Instead, motivational load represents an interaction between the demands of the task, and the predicted motivational characteristics of the learner. Because of recent innovations in the measurement of mental effort, cognitive load, and cognitive workload as well as well-established measure of goal orientations, self-efficacy, ability and emotionality, such a model may now be both plausible and possible.

Conclusion

The literature examining motivation in learning environments provides important insightsinto human behavior; allowing prediction of goal-related behaviors that relate to achievement. This body of literature has, until quite recently, been notable for the degree to which lines of research were pursued with little attention to an overarching theoretical framework. By developing such a framework, here described as motivational load theory, researchers may accomplish three ends. First, they may enrich the understanding of previous findings by interpreting prior evidence with respect to the indexes of motivation discussed above. For example, seen in the light of a curvilinear relationship between mental effort and task difficulty, prior evidence related to optimal difficulty levels may be subject to re-analysis and re-interpretation. Second, researchers may develop new lines of inquiry or experimentation that seek to establish the relationships between well-understood constructs such as self-efficacy or goal orientations and the indexes of motivation that help to predict future learning behaviors. By using the indexes of motivation discussed in this paper – choice, mental effort and persistence – as dependent variables, a large number of causal pathways related to learner motivation could be investigated. For example, a pathway from task-specific efficacy and goal orientation through emotional state and cognitive load might predict mental effort. Alternatively, a hypothetical path from emotional state and goal orientation might predict persistence and/or active choice could be tested using tools that are currently available. Finally, using a theory of motivational load with choice, effort, and persistence as its core constructs may expand the landscape of possibilities for conceptualizing the range and nature of independent variables that affect motivation to learn. Seen in the light of these three ends, this paper is offered as an invitation to engage in a dialogue about motivational load, and as a preliminary model to facilitate such a discussion.

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