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REVIEW ARTICLE

Cognitive Load as Motivational Cost

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Abstract
Research on cognitive load theory (CLT) has focused primarily on identifying the mechanisms and strategies that enhance cognitive learning outcomes. However, CLT researchers have given less attention to the ways in which cognitive load may interact with the motivational and emotional aspects of learning. Motivational beliefs have typically been assumed to be merely a precursor to the cognitive process. This view provides an incomplete picture of the dynamic relationship between cognitive load and motivational beliefs. In this review, we synthesize previous scholarly efforts concerning the motivational effects of anticipated investment of mental effort, new developments in the expectancy-value theory of motivation, and recent findings implicating cognitive load in the formulation of motivational beliefs. By conceptualizing cognitive load as motivational cost, we argue that motivational beliefs are an important outcome that results from instruction. We examine recent empirical evidence supporting this proposition and consider the implications for the further development of both CLT and motivational theories through their integration.

Keywords Cognitive load theory · Expectancy value cost theory · Motivation · Self-efficacy

Cognitive load theory (CLT) has evolved over the past three decades to become a major framework for understanding the impacts of instruction and instructional materials on learners' success. However, despite broader recognition that learning functions entail the integration of both cognitive and noncognitive processes (Plass and Kaplan 2015), most CLT research focuses solely on the relationship between working memory demands, schema formation, and subsequent performance without consideration of the interactions between cognitive load and motivation or emotion during learning. Initial assumptions about motivation in CLT research held that (1) sufficient motivation was a necessary precursor to learning and (2) adequate motivation could be asserted by virtue of study participants' investment of sufficient effort to complete and learn from presented tasks (Paas et al. 2005; van Merriënboer and

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Sweller 2005). For example, Paas (1992) asserted that “the subjects’ motivational state is expected to be high and equally divided across the experimental conditions” (p. 429) and concluded that the findings “complie[d] with the assumption of equally divided motivation” (p. 433).

In more recent research bridging CLT with affective states, studies have examined the effects of emotion and other constructs concurrent with issues of cognitive load in the design and delivery of instruction (e.g., Cognitive-Affective Theory of Learning with Media [Moreno 2006; Park et al. 2014]). For example, studies of emotional design in digital environments found that materials using warm colors and round, face-like shapes induced positive emotions and were associated with stronger performance on comprehension assessments when compared with neutrally designed environments (Plass et al. 2014; Um et al. 2012). These studies further found that positive emotions were associated with a decreased perception of task difficulty. In contrast, Knörzer et al. (2016) found that induced negative mood facilitated stronger comprehension performance than induced positive mood and that positive mood was associated with greater perceptions of task difficulty. These studies also examined potential interactions between task motivation and cognitive load, but they did not find significant effects. However, in each, affective processes were considered to function in parallel to the investment of effort during the learning phase.

To date, however, few studies have conceptualized motivational beliefs as an outcome of instruction that can be mediated by cognitive load. The current review examines new directions for CLT research that conceptualize motivation as an outcome of cognitive load, rather than a precursor or parallel process. Synthesizing prior research regarding the motivational impacts of anticipated investment of mental effort (Cennamo 1993; Salomon 1984), new developments in the expectancy-value theory of motivation (Barron and Hulleman 2015), and recent findings documenting changes in motivational beliefs associated with differing levels of cognitive load (e.g., Feldonet al. 2018; Likourezos and Kalyuga 2017), we argue that motivational outcomes are an important and promising area of further development for cognitive load theory.

Cognitive Load Theory

Cognitive load theory provides a theoretical framework for examining and leveraging cognitive processing demands during learning (Paas and van Merriënboer 1993; Sweller 1988, 2010; Sweller et al. 2011; van Merriënboer and Sweller 2005). Central to CLT, working memory is limited in both capacity and duration (Cowan 2001; Martin 2018). In general, working memory processing capabilities allow individuals to process only small quantities of information at any given time and retain them for approximately 20–30 s without rehearsal (Adams et al. 2018). As a result, working memory selectively filters information to be encoded into long-term memory, and instruction that exceeds working memory capacity will be ineffective (Sweller 2004). However, relevant and well-structured prior knowledge increases the functional capacity of working memory relative to the task, affording individuals with greater expertise a lower burden on working memory than those with less expertise (Feldon 2007; Gobet 1998; Ericsson and Kintsch 1995; Sweller 1994).

Cognitive load is a multidimensional construct involving both load and effort (Paas 1992; Paas et al. 2003). Paas (1992) defines mental *effort* as the cognitive resources utilized and allocated for learning. Thus, the amount of mental effort invested in a task can be a reliable estimate of a learner's motivation for a task (Paas et al. 2005). The cognitive *load* is the total burden placed on working memory by the instructional materials in the context of the learner's prior knowledge (Ayres 2018; Kalyuga and Plass 2018). Paas (1992) argues that mental load is often imposed by "instructional parameters (e.g. task structure, sequence of information), and mental effort refers to the amount of capacity allocated to the instructional demand" (p. 429). CLT posits that as cognitive load increases, due to either poorly designed instruction or complexity of target content (i.e., element interactivity), learning becomes less efficient, because meeting the imposed demands on working memory occupies resources necessary for encoding and refining schemas in long-term memory (Paas et al. 2003).

Types of Cognitive Load

Historically, CLT has specified three types of cognitive load: intrinsic, extraneous, and germane (Kester et al. 2010). Intrinsic load customarily refers to the inherent complexity of the content, extraneous load refers to sources of demand on working memory that do not enhance learning, and germane load refers to instructionally beneficial information that facilitates efficient learning. More recent perspectives (e.g., Kalyuga 2011; Sweller 2010) suggest that intrinsic load may be more appropriately operationally defined as the load imposed by effective instruction relative to the prior knowledge of the learner. This shift consolidates the original concepts of intrinsic and germane load and eliminates the critique that the three types of load were not of "like kinds" (Gerjets et al. 2009). Thus, in this paper, the load imposed by interacting elements in content during learning will be referred to as intrinsic load, and features and processes of instruction that facilitate learning through the use of working memory will be referred to as the use of germane resources (Leppink et al. 2014). Regardless of how they are parsed, the types of cognitive load are additive, such that in any proportion, the aggregation of all sources of load must not exceed the capacity of learner's working memory in order for successful learning to occur (van Merriënboer and Sweller 2005).

Several measurement efforts have attempted to use self-report instruments to differentiate between types of cognitive load (Ayres 2006; Hart and Staveland 1988; Gerjets et al. 2006; Leppink et al. 2013). Ayres (2006), for example, created a rating scale to evaluate intrinsic load, while holding extraneous load constant. He found a strong positive correlation between error rates and difficulty ratings. However, results also indicated that participants' ability to accurately rate cognitive load was dependent upon their level of expertise. More recently, Leppink et al. (2013) analyzed multiple factors for each type of load based on participants' responses to a 10-item scale. Items assessed intrinsic load based on items related to the complexity of the instructional content, extraneous load based on participants' perceptions of the negative attributes of information presented during instruction, and germane load based on perceived contributions of the instructions and explanations during the learning activities. Results for each factor were consistent with the a priori expectations of cognitive load distribution based on differing instructional formats.

In a second study, Leppink et al. (2014) modified the scale to include an item targeting mental effort explicitly in each factor. Consistent with their previous findings, the results indicated that the instrument effectively differentiated between intrinsic, germane, and extraneous load items based on a robust three-factor structure. Results suggested that the added mental effort items increased the reliability of the factors for intrinsic and extraneous load but not for germane load. However, the factor scores representing extraneous and intrinsic load did not reflect the difference in the performance outcomes associated with variations in instructional conditions. Conversely, the germane load factor did reflect differences in performance, as learners who reported high levels of germane load scored higher on the performance assessment.

Collectively, the results offer some support for the assumption that it is possible for learners to differentiate between intrinsic and extraneous cognitive load using a self-report instrument. However, findings also suggested the factors used to represent intrinsic and extraneous load were highly correlated, indicating that participants might have had difficulty differentiating between the two types of load. Moreover, Leppink et al. (2014) noted there were doubts regarding whether the factors identified definitively represented the three types of load and called for further experimentation to evaluate the validity of this assumption.

Mental Effort, Cognitive Load, and Motivation

The relationship between mental effort and cognitive load establishes a natural nexus between cognition in working memory and motivation. Three robust indicators of motivation—goal selection, mental effort, and persistence—are each fundamentally tied to the investment of mental effort, which reflects a willingness to fully engage under the demands of the cognitive load imposed by a learning context (Pintrich 1990; Schunk et al. 1996; Wigfield and Eccles 2000). These can respectively be operationalized as the decision to invest effort in pursuit of a specific goal, the willingness to expend mental effort, and the willingness to sustain effort investment until a goal is attained.

Extensive research in the field of motivation has identified specific motivational beliefs that are positively associated with effort investment, consistent with Paas's (1992; Paas et al. 2005) assumptions. These include forms of expectancy—notably self-efficacy—and the perceived value of tasks in terms of either intrinsic merits or utility in the context of pursuing other goals (Eccles and Wigfield 2002; Wigfield and Eccles 2000). Self-efficacy beliefs (i.e., one's perceptions regarding one's ability to successfully accomplish a specific task) influence the investment of mental effort, because if learners do not "believe they can produce the desired effects by their actions, they have little incentive to act" (Bandura et al. 1996, p. 1206).

Further, just as relevant prior knowledge mitigates the level of cognitive load imposed on individuals, it also affects motivational beliefs. For example, in a review of literature on academic interest, Tobias (1994) concluded that prior knowledge accounted for approximately 20% of the variance in students' interest in a learning process. Similarly, knowledge of tasks gained through past experiences contribute to higher goal aspirations and a greater investment of mental effort (Bandura 1997). However, Hailikari et al. (2008) found that motivational self-beliefs (self-efficacy, expectations of success, and perceptions of math ability) did not directly predict mathematics performance. Instead, prior knowledge relevant to the learning material moderated the influence of motivation on performance. Further, Heggestad and Kanfer (2005) suggest that self-efficacy is a "consequence rather than a cause of performance" (p. 95).

Following this line of thought, several additional studies examining the relationship between self-efficacy, invested effort, and performance conclude that self-efficacy does not account for significant variance in subsequent performance after controlling for the influence of past performance (Vancouver et al. 2001, 2002; Yeo and Neal 2008). In these studies, as students' self-efficacy increased on the basis of positive feedback, their performance deteriorated over time. Vancouver et al. attributed the decline in performance to "an inflated belief in capacity via an intervention targeted to increase self-efficacy without a commensurate improvement in effectiveness" (p. 514). In cognitive terms, the increased task knowledge from feedback led to a reduced estimate of necessary mental effort for completion of the task, which is inconsistent with Bandura's (1997) and Paas et al.'s (2005) assumptions that motivation (primarily self-efficacy) predominantly drives the level of effort invested. It appears instead that individuals' estimated levels of necessary effort based on prior knowledge may be the better predictor of invested effort.

Anticipated Investment of Mental Effort

Motivationally, learners' beliefs about the necessary level of effort to invest in a learning task are of fundamental importance. Comparably, CLT assumes that for effective instruction to occur, the learner must be sufficiently motivated to invest the mental effort necessary to meet the demands imposed by the task (van Merriënboer and Sweller 2005). As described above, the willingness of the learner to engage in the learning task is a fundamental indicator of motivation. Thus, if the learner perceives the task to be too difficult, it could result in lack of engagement (Clark 1999).

In this regard, anticipated investment of mental effort (AIME; Salomon 1983) provides an explanation of the relationships among mental effort, learning, and instructional material. Salomon's (1984) argument is that learners make anticipatory judgments regarding "the perceived attributes of the instructional procedures, and subsequently expend mental effort accordingly" (p. 649). He identified two factors that influenced AIME: the perceived cognitive demand characteristic of the task (i.e., anticipated cognitive load) and learners' self-efficacy. When students perceived the nature of the instructional format to be easy (i.e., television, as opposed to print), they invested less mental effort during learning and scored lower on the subsequent assessment. In contrast, when they perceived print-based instruction as more demanding, they invested greater mental effort, and achieved higher scores on the subsequent assessment, despite the fact that the content delivered was identical across the two types of media. Moreover, in the print condition, self-efficacy correlated positively with both mental effort and achievement, but in the video condition, it correlated negatively (Salomon and Leigh 1984). Thus, students who participated in the televised instruction condition reported higher levels of self-efficacy, despite poorer performance.

Similarly, Cennamo et al. (1991) examined learners' preconceptions regarding learning outcomes through television, print, interactive videos, and computers. They also identified an interaction between the medium used to present identical content and participants' learning outcomes. Specifically, participants reported having more difficulty learning from books and computers than learning from television and interactive video. Cennamo (1993) argued three learner characteristics influenced preconceptions towards specific instructional medium, which, in turn, influenced AIME and learning: (1) perceived characteristics of the instructional medium, (2) the nature of the task, and (3) learner characteristics such as prior knowledge.

Thus, self-efficacy contributes significantly to the allocation of cognitive resources according to perceived task demands. A high level of self-efficacy would be accompanied by an anticipatory belief that the necessary level of effort for performance would be lower (e.g., Lawson et al. 2007; Salomon 1984), whereas a low level of self-efficacy would be accompanied by the anticipatory belief that the necessary level of invested mental effort needed for success would be higher (Yeo and Neal 2013). During learning and task performance, learners with high levels of self-regulation may be able to dynamically reassess their expectations of necessary effort and reallocate accordingly (van Merriënboer and Sluijsmans 2009). However, there seems to be a point when effort investment can no longer compensate for increases in task difficulty, which leads to effort cessation (Yeo and Neal 2008). This nonlinear relationship of effort investment and self-efficacy can be described as an inverted U-shaped curve (Beck and Schmidt 2018; Clark 1999). If the perceived cognitive load imposed by a given task exceeds a learner's working memory capacity, the individual might opt not to invest mental effort (Kimchi 1982; Yeh and Wickens 1988). In contrast, when learners perceive mental effort as unnecessary to achieve success, there is little or no effort investment (Cennamo 1993; Pintrich and Schrauben 1992).

When individuals develop skills and knowledge that support successful achievement, their perceptions regarding the effort necessary to successfully perform the task decrease, resulting in allocating less effort on subsequent tasks (Yeo and Neal 2008). For example, Likourezos and Kalyuga (2017) compared direct instruction and constructivist instructional approaches while students engaged in problems solving activities. Results suggested that participants' perceived mental effort and expected probability of task success (i.e., self-efficacy) were significantly different as a function of instructional condition. Participants who received guided, direct instruction with problem-solving examples reported investing less mental effort concomitant with higher levels of self-efficacy than the unguided problem-solving condition. However, the reduction in cognitive load did not result in improved learning outcomes.

Expectancy-Value Theory of Motivation

Expectancy-value theory (EVT; Eccles and Wigfield 2002; Wigfield and Eccles 2000) is one of the most prominent models of motivation, emphasizing the importance of believing one can succeed at a task (i.e., expectancy) and that the task is important (i.e., value). Thus, two prominent questions influence motivation: "Can I do this task?" and "Do I want to do this task?" (Eccles et al. 1998).

Although expectancy and value beliefs are important individually, a significant contribution of EVT is that it helps to describe the interaction among multiple motivational constructs (Eccles and Wigfield 2002). Thus, motivation is not determined solely by one's expectancy but by complex interactions among expectancy and value factors. For example, expectancy and value are both predictive of performance, behaviors, and beliefs (Wigfield et al. 2006). However, they play different roles. Expectancy beliefs tend to more strongly predict achievement, whereas value is more predictive of the activities one chooses (Wigfield et al. 2006). Further, in situations where individuals might hold low expectancy for success but high task value, they are more likely to engage in avoidance behaviors that would not manifest under other expectancy-value configurations (Jiang et al. 2018; Shah and Higgins 1997).

Expectancy

In terms of the first question, "Can I do this task?" expectancy is the key construct. Expectancy has been extensively studied within motivation literatures, encompassing several common terms. For example, within social cognitive theory, self-efficacy is often described as one's belief in his or her capacity to successfully complete a task at a given level (Bandura 1986, 1997). Essentially, self-efficacy and expectancy are equivalent constructs (Eccles and Wigfield

2002; Schunk and Pajares 2009), whether conceptualized at a general level (e.g., Luszczynska et al. 2005) or task-specific level (e.g., Schwoerer et al. 2005).

In addition to self-efficacy, expectancy within an EVT framework also overlaps significantly with some aspects of self-determination theory (SDT) which includes autonomy (i.e., experiencing volition or self-endorsement), relatedness (i.e., feeling accepted or connected), and competence (i.e., feeling effective) as three prerequisites of adaptive motivation. In particular, the need for competence refers to a desire to experience a sense of effectance and confidence in one's interactions with the environment (Ryan and Deci 2002). As such, expectancy and competence overlap significantly and the empirical findings on these two subjects are interchangeable.

Regardless of the specific terminology, expectancy variables are strongly linked with a variety of behavioral indicators of motivation, such as the activities one chooses, the level of engagement and persistence, and engagement in adaptive self-regulated learning (SRL) processes such as goal-setting and adaptive strategy use (Bong 2001; Davis-Kean et al. 2008; Denissen et al. 2007; Klassen and Usher 2010; Simpkins et al. 2006; Wentzel and Wigfield 2007). In addition, expectancy beliefs tend to be strong predictors of important outcomes such as academic achievement (Meece et al. 1990; Spinath et al. 2006) and decisions including the selection of college majors and career paths (Eccles et al. 2004; Simpkins et al. 2006).

One's expectancy for success develops from several sources including prior successes and failures, vicarious learning, encouragement from others, and physiological states (Bandura 1997; Chen and Usher 2013; Schunk and Pajares 2009). Prior successes and failures are the strongest determinant of expectancy (Bandura 1997). That is, when students succeed at a task, their expectancy for future success on that task increases, and expectancy decreases when they fail. In addition, vicarious learning, or learning from observing others, also influences expectancy. Specifically, when one observes an individual succeed, they experience an improvement in expectancy beliefs for success as well. This observational effect increases with a greater match between the model and observer (Schunk and Hanson 1985, 1989). Encouragement or positive persuasion from peers, parents, or teachers can also play a significant role in enhancing one's expectancy for success. Finally, one's expectancy can further be affected by the physiological and emotional reactions associated with an activity or a task, such as fear, stress, anxiety, or fatigue. That is, the physical experience of trembling while attempting to complete a tight rope walk can negatively impact expectancy for success.

Value

Value addresses the second core question of EVT, "Do I want to do the activity?" As is the case with expectancy, value also overlaps with constructs that are described within other motivational research models. This includes the need for autonomy, which is emphasized in SDT (Deci and Ryan 1985), as well as interest theories (Hidi and Renninger 2006), and achievement-goal theory (Ames 1992). Overall, value is the sum of three constructs, (a) intrinsic interest, (b) utility, and (c) attainment value.

The first component of value is intrinsic interest. Individuals who are intrinsically interested perform an activity because they find it to be inherently interesting or rewarding (Sansone and Harackiewicz 2000). Intrinsic motivation is generally emphasized to be highly adaptive (Ryan and Deci 2009) and appears to develop as a result of expectancy and experiences of success and failure. As children grow older, they tend to place greater value on the tasks in which they succeed and distance themselves from activities that are difficult (Covington 2009; Harter 2012). Intrinsic interest is important to EVT because people tend to perceive greater value for tasks in which they are intrinsically motivated. However, other components also play a role.

The second component of value is utility, which entails the perception that completing the task is important to the attainment of short- or long-term goals (Eccles and Wigfield 2002). Thus, utility is determined, in part, by one's personal goals, and in the absence of utility beliefs, learners display maladaptive motivation or disengagement from the task. For example, consider a medical student who perceives that studying for her courses will provide knowledge to better serve patients in the future. We would expect her to place greater value on that task and thereby be more motivated to study. In contrast, consider a middle school student who complains that her mathematics homework is not important because she will never need to balance equations in the future. This student is expressing lower perceived utility. Thus, she will likely be less motivated to do her math homework.

Utility is particularly important in the case of tasks that are not intrinsically rewarding. When an individual perceives utility, they may engage in that task even if is aversive. This is important for those activities that are beneficial (e.g., exercising) but may not always be pleasant (Vallerand 2001).

Attainment value is the third component of value, and it describes the extent to which successfully completing the task is in alignment with one's needs and personal and social identity. Consider, for example, how the attainment value of a specific task may vary among different athletes. Winning a foot race should hold greater attainment value to a runner than a weight lifter. Moreover, that level of attainment value is likely to differ even among runners, because winning a 100-m dash likely holds greater value for a sprinter than a distance runner. Because greater attainment value is expected to lead to greater effort and persistence, we would expect the sprinter to train harder and exert greater effort in an attempt to win the 100-m dash. Attainment value is related to one's self-image and self-knowledge. If one believes those abilities are consistent with one's own self-schema, the attainment value of that task increases (Eccles 2009; Eccles and Harold 1991).

Cost

Cost entails the effort needed to complete a task as well as what one must give up in order to complete the task (Eccles 2005). Historically, "cost" has been conceptualized as a subcomponent of value, with the weighing of costs and benefits for a specific endeavor informing assessments of utility and attainment value. However, some recent research suggests that cost appears to impact perceptions of both expectancy and value (Eccles et al. 1983). Moreover, psychometric evaluations of EVT measures have provided factor analytic support that cost is a unique factor (Chiang et al. 2011; Conley 2012; Eccles and Wigfield 1995; Trautwein et al. 2012). For example, Eccles and Wigfield (1995) conducted a confirmatory factor analysis and found ratings of task difficulty to be distinct from expectancy and value. In addition, Chiang et al. (2011) found similar results using an exploratory factor analysis (EFA) of a self-report questionnaire measuring expectancy, value, and cost. Specifically, the EFA suggested a two-factor solution with a "beliefs" factor consisting of expectancy and value items and a cost factor. Similar results were obtained by Conley (2012) in the domain of mathematics and by Trautwein et al. (2012) in both mathematics and English domains.

As a result of these recent findings, some researchers have proposed a revised model, the expectancy-value-cost theory (EVCT), in which cost is described as a unique, third construct

(Barron and Hulleman 2015). We use this more contemporary model to guide our understanding of motivation. In doing so, we engage an examination of the prospective relationships between these three beliefs and cognitive load.

Cost as an Emerging Construct Within EVT

Researchers tend to describe four key types of costs, such as effort, “outside effort,” loss of valued alternatives, and psychological stress. The relative weight or emphasis of these costs may depend on whether the outcome is a success or failure. When an attempt is successful, the effort invested and missed alternatives are viewed as a cost. For example, in order to win a marathon, one might be required to train regularly and exert high levels of effort on the day of the marathon. If effort exertion exceeds value components, one might be expected to stop training or stop running during the marathon. In addition, the time required to train for a marathon would result in the loss of valued alternatives such as missed opportunities to spend time with friends or family. Outside effort, another type of cost, accounts for the juggling of effort between multiple competing activities (Flake et al. 2015). For example, a college student majoring in art who feels that their art has suffered because of the inordinate effort they have invested to pass their general education mathematics requirement has experienced the cost of outside effort.

In relation to failure, one experiences heavy costs in the form of psychological stress. Although a range of psychological stressors or emotions may be present, such as frustration, disappointment, and sadness (Zeidner 2007), most of the research regarding psychological costs have focused on the anxiety one feels at the possibility of failing at the task. For example, pursuing a promotion at work may generate anxiety of failure. Costs associated with failures, such as anxiety, tend to be most significant in learning contexts that emphasize evaluation. Moreover, given that school becomes more evaluation driven and students experience greater frequency of failures in later grades, costs, such as anxiety, tend to become more prominent in middle school and high school (Zeidner and Matthews 2018).

While cost has received less empirical attention within the EVT literature compared to expectancy and value (Barron and Hulleman 2015; Flake et al. 2015; Wigfield and Cambria 2010), it does play an important role in determining motivation. In contrast to expectancy and value that positively relate to motivation, the relationship between motivation and cost tends to be negative (Eccles 1987). For example, cost predicts task avoidance. Chen and Liu (2009) found that costs, such as alternate activities and work load, were factors that accounted for variance in students’ decisions to not enroll in a physical education class. Similarly, students who identified higher costs of exercise tended to report exercising less, while students who reported higher levels of expectancy and value tended to report exercising more frequently (Chiang et al. 2011). Within academic contexts, students who perceive greater costs associated with specific endeavors are less likely to pursue related goals (e.g., take fewer mathematics classes [Luttrell et al. 2010]; attend graduate school [Battle and Wigfield 2003]) and more likely to fail to persist (e.g., intend to leave a science, technology, engineering, or mathematics college major; [Perez et al. 2014]).

Further, cost negatively correlates with other motivational beliefs (i.e., expectancy and value; Flake et al. 2015) and tends to mediate the relationship between expectancy and perceptions of necessary effort and task difficulty (Eccles et al. 1983). These findings are consistent with research regarding attributions (Weiner 1985) and mindset (Dweck 2006), which suggest that conceptions of effort and ability are negatively related. For example, attributing a success to effort may lead one to downplay innate ability. Moreover, individuals with a fixed mindset perceive that exertion of effort is indicative of poor ability (Dweck 2006).

A recent study by Jiang et al. (2018) provided additional support that cost may be better conceptualized as a third, core construct rather than a subcomponent of value. Specifically, the study examined the predictive value of expectancy, value, and cost for important academic outcomes. The results indicated that cost significantly and positively predicted maladaptive academic behaviors, such as setting avoidance goals and procrastination. It also significantly and negatively predicted achievement. Moreover, the authors compared the variance explained by cost and value as separate factors with the variance explained by a composite variable that collapsed cost and value. Both the variance explained and the stability of the predictions for both achievement and academic behaviors were higher when cost and value were disaggregated.

Cognitive Load as EVCT Cost

Within the motivational literature, cost as well as the other motivational variables are typically conceptualized as the aggregated perceptions of an individual that have trait-like properties, as opposed to state perceptions of cost for an individual event. Consider, for example, that Eccles and Wigfield (1995) measured EVT constructs with a 29-item questionnaire called the Self- and Task-Perception Questionnaire. This questionnaire addressed two facets of cost, task difficulty and perceptions of necessary effort. Three Likert items were used to measure students' perceptions of task difficulty for the domain of mathematics. One item identified task difficulty in general within mathematics, a second item examined task difficulty in relation to other students in class, and the final item was the task difficulty of mathematics in relation to other academic subjects. In addition, students responded to four items about the effort required to succeed in the domain of mathematics. The effort items addressed effort requirements for getting good grades, doing well in an advanced mathematics class, doing well on a test, and effort expenditure in mathematics compared to other academic subjects. These items were then averaged to generate a task difficulty composite and an effort composite, respectively.

The composites depicted how difficult one *tends* to perceive mathematics or the effort *generally* required for mathematics. There are advantages of conceptualizing task difficulty and effort as the aggregation across multiple activities within a domain. For example, doing so is often beneficial for measurement because the internal consistency of measures can be calculated easily. Moreover, conceptions of task difficulty and effort at the domain level tend to be predictive of other EVCT constructs and achievement (Eccles 1987; Perez, Cromley, & Kaplan, 2014). At times, it is also valuable to consider the task difficulty or effort expenditures required at the individual task-level. For example, within the domain of mathematics, one type of task (e.g., computation) may be easy for an individual while other tasks are difficult (e.g., word problems). However, generating composite scores that depict more global levels of task difficulty or effort does not identify the nuanced differences between these contexts. Moreover, these nuances may be relevant for identifying areas of difficulty for learners that require additional assistance or intervention. Upon creating composites, this variability is lost.

Thus, we argue that both general ratings and individual task-level data are important within an EVCT perspective. Furthermore, we perceive that task difficulty and effort at the task-specific level fundamentally overlap with cognitive load constructs. That is, we can conceptualize cognitive load as task-specific cost within the EVCT. When comparing tasks that have equal intrinsic difficulty levels (i.e., impose equal intrinsic cognitive load), those with less extraneous load could be conceptualized as lower difficulty and lower effort tasks. Conversely, those tasks with greater extraneous load would be higher difficulty and higher effort tasks.

Empirical Findings of Cognitive Load Effects on Motivation

Examination of those studies that have manipulated cognitive load with the intent of observing subsequent changes in motivation constructs provides promising initial evidence for an integrated EVCT-CLT perspective. For example, Steele-Johnson et al. (2000) found that manipulating the cognitive load associated with a learning task moderated the relationship between goal orientation and post-task self-efficacy, with higher levels of load associated with higher levels of self-efficacy for mastery goal-oriented participants compared to those with performance goal orientations. Conversely, participants with performance goal orientations reported significantly higher levels of self-efficacy than their mastery-oriented peers in the lower cognitive load condition. In this case, the study manipulated cognitive load by varying the level of consistency across learning tasks.

In a more conventional CLT study, Likourezos and Kalyuga (2017) compared outcomes for learners across three instructional conditions hypothesized to impose differential levels of extraneous load—fully guided instruction, partially guided instruction, and learning through problem-solving. Although they did not find differences in learning outcome by condition, they did identify significant differences in self-reported cognitive load by type (per Leppink et al. 2014), consistent with their expectations that both intrinsic and extraneous load would increase as the level of instructional guidance decreased. These differences in load did predict post-task self-efficacy (i.e., "probability of success"; p. 207), with lower levels of load predicting higher levels of self-efficacy, despite the lack of significant differences in learning outcomes.

Similarly, Feldon et al. (2018) reported the results of a quasi-experimental study where the two instructional conditions imposed comparable levels of cognitive load overall but manipulated the relative proportion of intrinsic and extraneous load. In this study, participants did differ significantly in their performance following instruction, with participants in the lower extraneous load condition scoring better on a subsequent performance-based assessment. These participants also demonstrated significantly greater pre-post gains in their reported self-efficacy ($d = 0.54$). To account for the variance in self-efficacy gain that differential learning outcomes may have contributed, task performance was used as a covariate when comparing pre-post self-efficacy gains across conditions. Supportive of the hypothesis that cognitive load imposed a direct effect on self-efficacy, the effect size of the relative gain between conditions increased to $d = 0.61$, favoring the condition imposing less extraneous load.

In contrast, Huang (2017) compared learning outcomes and self-efficacy across instructional conditions (peer modeling vs. worked examples), resulting in larger gains for both variables in the condition that imposed higher levels of cognitive load as measured using Paas's (1992) single Likert response item. However, the peer modeling condition appeared to recruit more germane resources by offering more instructionally beneficial features, so it can be inferred that the higher load represented intrinsic rather than extraneous load. To determine if the self-efficacy effects were influenced by participants' learning success, Huang (personal communication, October 12, 2018) re-analyzed the data reported in the 2017 study to include post-learning performance variables as covariates. Those results identified significantly greater self-efficacy gains in the higher load condition, net of any variance explained by learning outcomes, for retention ($d = 0.54$), and near transfer ($d = 0.59$) performance. The difference between conditions was not significant when the far transfer score was used as a covariate, but the similarities in effect sizes between the Feldon et al. (2018) and Huang studies are noteworthy.

The findings of Feldon et al. (2018) and Huang (2017, 2018) may appear upon first inspection to be in conflict regarding the role of cognitive load imposed by instruction in explaining self-efficacy change, because Feldon et al. (2018 identified greater gains associated with less cognitive load and Huang identified greater gains associated with more cognitive load. However, it is important to note that the lower level of extraneous load in the former study and the higher level of intrinsic load in the latter study are both associated with positive outcomes in accordance with the predictions of cognitive load theory, provided that total working memory capacity is not exceeded (van Merriënboer and Sweller 2005). Thus, it may be the case that learners derive their self-efficacy beliefs not from total level of cognitive load experienced but from the perceived benefit that accompanies that load. Consistent with the findings of Leppink et al. (2013, 2014), it may be that study participants differentiated between the types of load imposed and interpreted extraneous load as imposing greater cost than intrinsic load or the use of germane resources. Likewise, it is possible that a greater proportion of intrinsic load directly benefits expectancy beliefs.

This link between cognitive load and EVCT may offer several benefits to both fields of motivation and cognitive load theory. For example, conceptualizing extraneous cognitive load as a component of cost links the findings from the fields of motivation and cognitive load, facilitating communication and synthesis of empirical knowledge. In addition, while much of the prior literature has conceptualized motivation as a prerequisite to engagement with a high cognitive load task, newer research has examined the proposition that cognitive load can directly influence expectancy beliefs, independent of learning outcomes associated with instruction (Feldon et al. 2018). Conceptualizing cognitive load as a facet of cost can also facilitate experimental studies in which researchers can manipulate motivational cost experimentally through the manipulation of extraneous load and subsequently observe changes in other motivation variables.

Implications of an Integrated EVCT-CLT Framework

As noted, conceptualizing extraneous cognitive load as a component of cost within the EVCT model and measuring task-specific EVCT constructs may afford several benefits. Much work in CLT acknowledges the importance of motivation and its relationship with mental effort investment, but it has not deeply engaged with empirical investigation of that relationship (Schnotz et al. 2009). Similarly, recent efforts to understand the role of self-regulation in CLT have not yet directly engaged the interactions with motivation in that context (Boekaerts 2017; Seufert 2018). In the final section of this manuscript, we describe the potential benefits of this integrated perspective in greater detail and argue that task-specific measures of EVCT constructs might be most appropriate when examining experimental manipulations.

Experimental Manipulation of Cost

Much of the research examining the links among EVCT constructs has relied on correlational research methodologies. Research using experimental designs can also be important for identifying whether causal links exist among motivational processes. An obstacle, however, is that manipulating motivation states is challenging. For example, while manipulating task difficulty or effort, researchers may create multiple tasks that vary in difficulty but are parallel in content. Unfortunately, creating truly parallel items is not always feasible because items at various difficulty levels may unintentionally require different academic skills. For example, a mathematical computational task in which the easy task utilizes single-digit addition without regrouping, but the difficult item uses three-digit addition that now requires regrouping. These tasks, although similar, are not parallel.

Conceptualizing extraneous load as cost within EVCT may provide researchers with greater ability to examine motivational change experimentally as a function of task difficulty or required effort. For example, researchers could require participants to complete the same or very similar tasks with and without imposed extraneous load (e.g., collecting information across multiple displays). Upon doing so, the variations in task difficulty could be more objectively determined. This line of research is important to the cognitive load literature, motivation literature, as well as other related fields such as SRL. Recently, research within the fields of motivation and SRL have emphasized that students can, and often do, modify their approaches to tasks (e.g., the types and number of strategies they use) or adjust their motivation (e.g., expectancy) depending on task features (e.g., task difficulty, academic domain; Callan and Cleary 2018; Cleary and Chen 2009; Urdan and Midgley 2003).

Studying motivational changes as a function of imposed extraneous load could also be important and informative to researchers within the cognitive load literature as well. For example, it is relevant to understand whether completing a task with higher extraneous load has negative implications for motivation to engage in similar tasks in the future, as well as task-specific learning outcomes. For instance, cognitive load researchers can impose extraneous load in a variety of ways, such as deliberately invoking split-attention effects. Identifying whether different methodologies for imposing extraneous load have differential effects on motivation has important implications for instruction design and the pedagogical practices of educators. Likewise, better understanding the implications of intrinsic load and the use of germane resources for motivation constructs has potential to enhance both theory and practice for CLT.

Implications for Measurement

Conceptualizing cognitive load as cost could be further supported by using a wider array of measurement practices. For example, some researchers within the field of motivation and SRL have begun utilizing event-specific measurements of motivation and SRL that are administered while an individual is actively engaged in a task. Collectively, these measurement techniques have been called “event measures,” because they measure motivation or SRL in real time during a single event of interest (e.g., solving math word problems) as opposed to retrospective self-reports of general processes across a domain (e.g., Winne 2010).

One such technique, microanalysis, is a structured interview in which participants report their motivational beliefs, metacognition, and regulatory processes, just before, during, and after a task of interest. The timing of microanalysis measurement administration is linked with SRL theory (i.e., Zimmerman 2000) through the premise that some SRL and motivational processes are most prominent at specific times. For example, having adaptive self-efficacy just prior to task engagement sets the stage for adaptive planning in which learners focus on strategies and aim for challenging, mastery goals. Moreover, other processes are most important during a task (i.e., using strategies to manage cognitive resources) or just after task engagement (i.e., reflecting about successes and failures). Further, compared to questionnaires that aggregate across multiple contexts, event measures produce very fine-grained data that have been shown to be more sensitive to intervention change (Cleary et al. 2017).

The timing of motivational microanalysis within a study is similar to that of measures of cognitive load such as Paas's (1992) single-item measure, which can be administered intermittently during learning, after every individual assessment item in a set, and/or at the conclusion of an instructional period or unit (e.g., DeLeeuw and Mayer 2008). Likewise, dual task strategies for measuring cognitive load fluctuations in real time, such as finger tapping in a rhythm (Park and Brünken 2015) or measuring reaction time to an auditory tone during learning (Brünken et al. 2003), can capture changes in working memory demand over the course of a single task.

As such, motivational event measures could be used to measure variations or changes in motivational beliefs within a single task of interest in response to manipulations of extraneous cognitive load. Conversely, such measures could be used concurrently with various modes of cognitive load measurement to explore the dynamic interactions between load and motivational beliefs within a learning task that could shape load-driven changes in motivational beliefs. Further, if cognitive load is considered a manifestation of cost under EVCT, then studies of motivation during instruction do not need to rely exclusively on self-reported perceptions of task difficulty and effort. Instead, self-reported perceptions of cost and behavioral or physiological types of cognitive load data could be examined concurrently to create a more accurate picture. Doing so could help to further understand the complex interactions task features, motivational variables, learning behaviors, and achievement.

Conclusion

In this review, we have highlighted both the theoretical and empirical compatibilities of considering cognitive load imposed during instruction as a relevant form of motivational cost and informative to learners' expectancy. Strategies for engaging issues of motivation within the context of CLT research have evolved from early assumptions of motivation as a learning precursor to an interacting facet of learning concurrent to the impacts of cognitive load. We argue that further evolution of this perspective to one in which motivational beliefs are a direct consequence of cognitive load manipulation presents an important new direction that can benefit both the further understanding of cognitive load's role in impacting the efficacy of instruction and the further development of emerging research in the theory of motivation. While empirical findings in support of this proposition are currently limited, multiple studies offer evidence that cognitive load has a direct effect on motivational beliefs, independent of learners' post-instruction performance (e.g., Feldon et al. 2018; Huang 2017; Likourezos and Kalyuga 2017). As such, further research can extend understanding of this relationship.

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