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REFLECTION ON THE FIELD

Rethinking the Boundaries of Cognitive Load Theory in Complex Learning

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Abstract In the traditional framework of cognitive load theory, it is assumed that the acquisition of domain-specific knowledge structures (or schemas) is the only instructional goal, and therefore, the theory is applicable to any instructional task. Accordingly, the basic concepts of intrinsic (productive) and extraneous (unproductive) types of cognitive load were defined based on the relevance (or irrelevance) of the corresponding cognitive processes that impose the load to achieving this universal instructional goal, and the instructional methods advocated by this theory are aimed at enhancing the acquisition of domain-specific schemas. The paper suggests considering this goal within the whole variety of possible specific goals of different learner activities that could be involved in complex learning. This would result in narrowing down of boundaries of cognitive load theory and have implications for distinguishing types of cognitive load, sequencing different goals and instructional tasks, considering the role of learner expertise, and other aspects of complex learning. One of the consequences of this reconceptualization is abandoning the rigid explicit instruction versus minimal guidance dichotomy and replacing it with a more flexible approach based on differentiating specific goals of various learner activities in complex learning. In particular, it may allow reconciling seemingly contradictory results from studies of the effectiveness of worked examples in cognitive load theory (supporting the initial fully guided explicit instruction for novice learners) and studies within the frameworks of productive failure and invention learning that have reportedly demonstrated that minimally guided tasks provided prior to explicit instruction might benefit novice learners.

Keywords Cognitive load theory · Instructional guidance · Instructional goals · Explicit instruction · Initial problem solving · Expertise reversal effect

Cognitive load theory is an instructional theory that considers instructional implications of major characteristics of human cognitive architecture, primarily two of its most important

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components—working memory and long-term memory (see Sweller et al. 2011, for a recent overview of the theory). Working memory is a workplace of cognition in which we consciously and intentionally process information and construct new knowledge. Its major characteristics are very limited capacity and duration when dealing with new information (e.g., Baddeley 1986; Cowan 2001). Long-term memory represents a permanent repository of knowledge, most importantly—organized knowledge structures or schemas that allow us to categorize information in order to guide behavior. This knowledge base plays a critical role in lifting working memory limitations when dealing with familiar information. In cognitive load theory, cognitive load is defined as working memory load which is determined by the working memory resources required for performing a cognitive task by a learner. While intrinsic (productive) load is defined as the load imposed by cognitive processes that are relevant to learning, extraneous (unproductive) load is caused by cognitive processes that are unnecessary for learning (e.g., see Kalyuga 2011; Sweller 2010 for recent discussions of some basic definitions related to the above concepts).

The reconceptualization of cognitive load theory proposed in this paper was triggered by the attempts to reconcile some empirical evidence that seemingly contradicts established findings of this theory. The traditional view of cognitive load theory is that novice learners always require comprehensive explicit instruction that describes all the targeted concepts and procedures without a need for the learners to infer anything on their own, before they solve similar or transfer tasks independently (the worked example effect in cognitive load theory, Cooper and Sweller 1987; see Sweller et al. 2011 for an overview). Accordingly, the explicit guidance could be removed only in the following phases of instruction when the learners have acquired some task-specific knowledge. However, the results of a series of studies within the frameworks of productive failure and the preparation for future learning or invention learning (e.g., Kapur 2008; Schwartz and Bransford 1998) have seemingly demonstrated that the minimally guided learning tasks provided prior to explicit instruction (during the so-called generation phase) may be more beneficial for novice learners than starting with explicit instruction. These results apparently contradict cognitive load theory.

In cognitive load theory, the theoretical argument in favor of the explicit initial instruction is based on the eliminated or reduced extraneous cognitive load that would otherwise be imposed by mental search processes inevitably involved in dealing with less-guided tasks (e.g., when using means-ends analysis or trial-and-error techniques in the absence of relevant prior knowledge or instructional guidance). The reduced load enhances acquisition of domain schemas, as at each step of explicit instruction, learners attend only to a specific problem state and associated move (Sweller et al. 2011). Within a cognitive load framework, Van Gog et al. (2011) demonstrated inferior learning from problem–example pairs in comparison to example–problem or example-only instruction. Among the suggested potential explanations was novice students' inability to study the following example properly due to their failure to recognize deficiency in their problem-solving performance or due to the belief that they would have been capable of solving the problem correctly or reduced motivation to study the example due to failed problem-solving attempt. All these explanations contradict the conclusions from the alternative frameworks of productive failure and invention learning.

To resolve this contradiction, a closer look was taken at specific goals of different phases in alternative sequences of explicit instruction and independent problem solving and, more generally, in all complex learning tasks. Complex learning in this context refers to the tasks that involve multiple learner activities that may have different goals. The traditional framework of cognitive load theory is based on the assumption that the acquisition of domain-specific schemas in long-term memory is the only goal of any instructional task. Accordingly, the basic concepts of intrinsic and extraneous types of cognitive load are defined based on the relevance (or irrelevance) of the corresponding cognitive processes that impose those types of load to achieving this universal instructional goal, and the instructional methods advocated by this theory are aimed at enhancing the acquisition of domain-specific schemas.

If this assumption is lifted, the above goal should be considered within the whole variety of different specific goals and corresponding learner activities that allow achieving these goals (and thus potentially contributing to relevant, productive load), especially in complex learning environments that usually involve multiple activities and goals by definition. In this case, the boundaries of cognitive load theory need to be narrowed down, and some of the theory's basic approaches should be reconsidered, even though mostly within the established range of its fundamental principles. This paper describes the resulting reconceptualization of cognitive load theory.

The proposed reconceptualization has implications for defining types of cognitive load, sequencing different goals and learner activities, considering the role of different levels of learner prior knowledge (or expertise), and other aspects of complex learning. One of the consequences of this reconceptualization for complex learning is abandoning the rigid explicit instruction versus minimal guidance dichotomy and replacing it with a more flexible approach based on differentiating specific goals of various learner activities (Kalyuga 2015). In particular, as mentioned above, it potentially allows resolving seemingly contradictory recommendations from studies of the effectiveness of worked examples in cognitive load theory (the worked example effect) and research results within the frameworks of productive failure and invention learning (if they are consistently replicated in controlled experimental studies). The paper starts from arguing about the required changes in cognitive load theory, then describes the suggested modifications of the theory, and concludes by discussing possible implications of the proposed reconceptualization.

Differentiating Instructional Goals in Complex Learning

Traditionally, cognitive load theory has always considered the acquisition of domain-specific knowledge—the knowledge associated with specific task areas in a specific domain—in the form of schemas in long-term memory as a single and uniform goal of any instructional task (e.g., Sweller et al. 2011). Accordingly, novice learners are not advised to be involved in learning tasks that would require any forms of search processes for achieving this goal, as such activities could lead to increased working memory load; the required information should rather be presented to them explicitly by instruction (Sweller et al. 2011; Sweller et al. 2007). Indeed, if the acquisition of domain-specific schemas is the only instructional goal to be achieved, this advice has a robust evidence-based support from research in worked example effect in cognitive load theory. Any alternative approaches that involve problem-solving search and exploratory activities would not be efficient ways of learning the required domain-specific schemas due to heavy extraneous (unnecessary) cognitive load (Sweller 1988). The effectiveness of explicit instruction in such situations (e.g., using worked examples, case studies, etc.) has been well acknowledged in cognitive load theory and in instructional science beyond it (e.g., Schmidt et al. 2007; Hmelo-Silver et al. 2007; Van Merriënboer and Kirschner 2007).

As a result of this exclusive focus on the acquisition of domain-specific schemas, cognitive load theory has not paid much attention to possible differences between specific goals of different activities involved in learning and instruction, assuming that principles of this theory are applicable universally or, as critically noted by Kuhn (2007), “irrespective of what is being taught to whom or why” (p. 109). Some of such goals may indeed differ from the acquisition of domain-specific schemas and therefore require corresponding learner activities and instructional methods for their achievement that are different from the activities and methods that are best suitable for learning domain-specific schemas. It becomes especially evident with a shift from relatively simple, single-goal instructional tasks that occupied most of early research in cognitive load theory (e.g., solving an algebra equation of the type $ax = b$) to more complex, multi-goal learning environments (e.g., working on a simulated environmental project or complex science problem).

Complex learning tasks and environments—particularly those implementing problem-based learning or inquiry learning approaches—usually require learner participation in various learning activities with different specific goals that could be different from the immediate acquisition of domain-specific schemas. For example, the goal of the initial discussion which is usually involved in problem-based learning environments is activating and sharing prior conceptions and intuitions (Schmidt et al. 2009), including partially relevant or even incorrect prior knowledge which may also enhance further learning (De Grave et al. 2001; Capon and Kuhn 2004; Schmidt et al. 2007), for instance, when a conceptual change should be achieved—in such cases, incorrect conceptions have to be activated; otherwise, they would not be modified or replaced (resulting in no conceptual change).

For illustrative purposes, a possible simplified and rough differentiation of instructional goals in complex learning could involve the following three major levels. The lower-level goals (“pre-instruction goals”) could be related to creating necessary cognitive or motivational prerequisites for learning prior to the acquisition of domain knowledge. Examples of such goals (taken from the suggested goals of initial phases of instruction in productive failure or invention learning approaches) could be intentionally activating relevant prior knowledge, enhancing learners’ awareness of the problem situation and own knowledge gaps, or focusing their attention on searching for deeper patterns rather than surface characteristics or procedures. These goals do not assume learning of something but rather creating conditions for future learning. The goals of motivating to learn and engaging with the learning task may also belong to this level.

The next level includes the goals of acquiring domain-specific concepts and procedures (usually evaluated by retention or near transfer tests using tasks that are similar to those presented during instruction) that are traditionally considered in cognitive load studies. Finally, the third level—higher-level goals—may relate to learning generalized concepts and strategies in a domain (e.g., general conceptual frameworks, domain principles, and heuristics) as the basis of flexible performance in this domain evaluated by far transfer tests within the broader domain (using tasks that are different from those presented during instruction, but still based on the same general frameworks and principles of the domain).

The first and third levels in this taxonomy (the level of “pre-instruction” goals and the generalized domain level) are the levels of goals that have not been usually considered in cognitive load research. A more refined taxonomy of specific goals and the corresponding learning tasks and activities that could be used to efficiently achieve these goals needs to be further clarified and developed. However, even based on this rough classification, it is evident that the immediate acquisition of domain-specific schemas is not the only specific goal of any learning activity or instructional task. With other types of goals, even novice learners may potentially be involved in problem-solving search and exploratory activities without formally violating principles of cognitive load theory—as those principles may simply not apply in these situations that could therefore be beyond the boundaries of cognitive load theory.

For example, using a relatively simple learning task for the illustration, if the specific goal is to teach the solution schema for the basic linear equations such as $3x = 4$ (i.e., divide the right-hand side quantity by the coefficient on the left-hand side), worked examples could evidently be the most effective and efficient method to teach novice learners, and this concurs with the worked example effect in cognitive load theory. However, if the specific goal is to enhance learner awareness of the problem situation or own knowledge gaps, or activate potentially relevant prior knowledge, the initial exploration of the problem could possibly be effective in achieving such goals. Asking novice learners to solve the equation would most likely trigger applying a trial-and-error procedure by randomly testing different values for x, which would effectively demonstrate the dependencies between the elements of the equation and relations between both sides of it—exactly what is required to understand the nature of this problem situation and missing knowledge. Such activities as well as performing basic computation skills could contribute to activating the relevant prior knowledge.

Thus, it is possible that search-based problem-solving and exploratory activities may potentially be effective means for achieving some specific goals different from the acquisition of domain-specific solution schemas which has been the focus of cognitive load theory from its inception. Therefore, the boundaries or conditions of applicability of cognitive load theory need to be clearly defined, and considering instructional goals of specific learner activities involved in complex learning tasks could be critical for this definition.

It should be noted that the need to consider different goals of instruction over time and at different phases of cognitive skill acquisition was discussed in Renkl and Atkinson's (2003) fading model (see Renkl 2014 for a newer version of this model). It suggests that in different phases, there are different main goals for the learners to achieve (e.g., understanding at earlier phases or automating at the final stage). Accordingly, a fading procedure was proposed in which problem-solving elements were successively integrated into worked examples until the learners could solve problems independently. In this model, the differences in goals are related to differences in what should be presented to the learners according to the guidance fading procedure. Renkl and Atkinson (2003) also suggested that because of these differences in instructional goals, in contrast to the earlier stages of skill acquisition, different learner activities during the later stages contribute to productive or extraneous (unproductive) cognitive load.

Within the Knowledge–Learning–Instruction (KLI) framework, Koedinger and McLaughlin (2014) also noted that "it is important to lay out specific knowledge goals that a STEM course should address and then link them to appropriate instructional activities" (p. 70). For example, by considering the differences between the testing effect and worked example effect, they indicate that the testing effect is focused on learning facts, while the worked example effect is focused on learning schemas and procedures—therefore, the knowledge acquisition goals are different (facts vs. skills). Accordingly, the optimal learning tasks and instructional methods are also different (memorization via spaced retrieval practice vs. induction via example study and comparisons). Thus, according to "KLI Dependency" principle, the choice of instructional method depends on the specific knowledge acquisition goal: different knowledge goals require different learning processes leading to different optimal instruction approaches (Koedinger et al. 2012). Based on this principle, the above two methods differ in the type of targeted knowledge (facts vs. procedural knowledge, skills) and the type of required learning processes (facts require memorization, skills require induction). To achieve these different learning goals and processes, different instructional methods would be optimal—accordingly, tests would better enhance fact memory, and examples study would better enhance skill induction (Koedinger and McLaughlin 2014).

The Role of Specific Goals in Approaching Cognitive Load Phenomena

An essential concept in cognitive load theory that has traditionally been used for describing sources and the magnitude of cognitive load is the level of element interactivity—the degree of connectedness between the elements of information that need to be processed simultaneously in working memory (Sweller 1994, 2010). This concept has been often used in cognitive load research for roughly estimating potential cognitive load that could be imposed by specific learning tasks on learners with expected levels of prior knowledge. However, theoretically, it might be difficult to describe the whole variety of cognitive processes in the learner's mind that could potentially contribute to working memory load involved in a specific learning task by using only the precisely identified interacting "elements of information" and relations between them (the traditionally considered source of cognitive load). It may still be only a part or simplified version of the overall cognitive activity that comprises all the processes and operations occurring in learner working memory within some interval of time—a timescale of working memory operation—with the intent to achieve a specific goal.

For example, such processes may include relating or mapping different representations on each other, blocking irrelevant information, organizing words and images, selecting or encoding their components, linking them together and integrating with prior knowledge (which also needs to be activated and represented in working memory), making necessary inferences to construct mental representations, making abstractions, etc. Some of these processes are difficult (if possible at all) to describe in terms of clearly separated interacting elements of information. Ericsson and Kintsch (1995) theoretically described such processes in general as a sequence of related changing mental states in working memory. These mental states involve all the relevant cognitive components and events, including elements of external information as well as the activated prior knowledge structures from long-term memory.

Within this broader perspective, cognitive load could be theoretically considered as the intensity of the cognitive activity required for achieving a specific goal. It is determined by all the cognitive processes that need to be performed within the timescale of working memory operation for achieving this goal. Although it is impossible to provide precise values for this timescale, it could be generally considered as a matter of seconds when dealing only with novel tasks. For example, around 20 s was suggested in classical studies of the duration of short-term memory for the simple task of storing random sets of letters in the absence of intentional rehearsal by Peterson and Peterson (1959). When studying complex learning materials, the processing flow will usually shift attention to new information well before the above 20 s is over, in particular when the currently processed information is not central to the task. In addition, many working memory models claim that not only holding and processing information but also inhibiting currently irrelevant information and shifting attention are important working memory functions (e.g., Diamond 2013; Miyake and Shah 1999). They could be especially relevant when different sources of information are to be integrated, as typical of many complex learning arrangements.

Based on the previously mentioned Ericsson and Kintsch's (1995) model (in particular, on their concept of long-term working memory), the duration of the mental states that contribute to cognitive load phenomena may depend on the presence of the previously acquired long-term memory structures. Such activated prior knowledge structures may significantly extend the timescale of working memory well beyond the abovementioned limits. Therefore, it is, in principle, impossible to provide any specific numerical value for this timescale without considering characteristics of a specific task and knowledge base of a specific learner. In general, the working memory timescale provides the measure of simultaneousness of processing for the description of cognitive load. The elements processed and other cognitive operations performed within this timescale could be effectively considered as simultaneous for this purpose. This theoretical notion of intensity of cognitive activity when determining the magnitude of cognitive load effectively combines the consequences of both limited capacity and limited duration of working memory. If intended operations are not completed within these time limits due to high intensity, further processing and understanding could be inhibited. This timescale makes cognitive load essentially a local, micro-level characteristic of intensity of working memory processes during a relatively narrow time range.

It should be noted that the idea that not only the amount of information to be processed, but also time is the main determinants of cognitive load has been around for some time, however mostly in experimental psychology studies of working memory rather than in instructional psychology (e.g., Barrouillet et al. 2004; Barrouillet et al. 2007). Of course, the actual magnitude of this time range (the timescale of working memory operation) and, accordingly, the practical meaning of the above “locality” depend on the involvement of knowledge structures activated in long-term memory and therefore could vary significantly. It could be considerably prolonged and thus reduce cognitive load due to the chunking mechanism (or long-term working memory phenomenon according to Ericsson and Kintsch 1995) when dealing with familiar tasks. For example, when dealing with tasks exclusively within their area of expertise, due to the available extensive relevant knowledge base, experts may not experience any duration or capacity limitations of working memory—they may be able to maintain in active state virtually unlimited information encapsulated into familiar schemas for as long as they need. However, as soon as some unfamiliar information enters the task, the limitations of working memory inevitably come into play, thus narrowing the timescale and capacity of working memory operation.

The above notion of intensity as the magnitude of cognitive load has more theoretical rather than practical value. It essentially indicates what needs to be considered ideally to understand the nature of cognitive load phenomena. However, practically, the idea of element interactivity is probably the best approximation that we currently have to make some rough realistic estimates of cognitive load. This approximation obviously ignores some processes and operations involved, as well as the timescale on which they occur, as those are practically impossible to precisely describe and quantify. The best we can do with the element interactivity approach is to describe chunks of elements that more knowledgeable learners may possibly possess that enable them to reduce the capacity and duration (timescale) pressures leading to reduced cognitive load for these learners.

Thus, the suggested definition of cognitive load is not intended to completely replace the concept of element interactivity with intensity of cognitive activity, but rather to be used as an abstract theoretical concept describing cognitive load phenomena—the abstraction that could be approximated in a practically usable way by the former concept. Introducing the intensity of cognitive activity required for achieving a specific goal could potentially explain the key role of goals (including instructional goals) in approaching cognitive load phenomena, as any cognitive activity is directly associated with the corresponding goal. The traditional element interactivity approach on its own could not allow this.

An important implication of the suggested approach to defining cognitive load is that the actual changes in cognitive load and their influence on specific learning outcomes occur on the timescale of working memory operation. The learning outcomes over longer periods of time and for larger instructional units depend on the sequence of such local effects, as each of them influences working memory operation and learning during the following activities in a cumulative way. For example, a local disruption of working memory operation due to excessively high intensity of the corresponding activities (a cognitive overload) at one point of time within the corresponding range according to the working-memory timescale for the learner could inhibit comprehension and learning at the following points of time. This would happen even if cognitive load conditions (intensity of the corresponding activities) by themselves are well within working memory limits at these following points.

Nevertheless, in traditional cognitive load studies, cognitive load is often treated at a macro-level associated with larger instructional units (e.g., complex tasks, a series of learning tasks, a whole topic, a lesson, etc.) and longer corresponding periods of time. In many situations, this approach may still work well enough as the average load over longer units may reflect variations on the smaller timescale. However, when we deal with achieving different goals over such longer periods of time and need to account for cognitive load involved in achieving each goal, the cognitive load consequences of the corresponding activities could be misinterpreted. For example, a worked example effect could actually take place for a specific type of goal with studying examples being superior to problem-solving activities but could be erroneously expected and not actually observed for other goals involved (e.g., see the linear algebra equation example provided earlier).

If cognitive load is a local-level phenomenon reflecting the cognitive cost of what is happening in learner working memory at a specific local interval of time (of course, with the actual timescale of this locality dependent on the above-mentioned factors such as the goal and nature of the task, and the relative level of learner expertise), the task of managing this load belongs to a micro- rather than macro-management level of tasks. This means that cognitive load should be managed within the timescale of working memory operation corresponding to a specific goal, task, and learner, rather than over larger instructional units corresponding to a sequence of goals and tasks.

Within a traditional cognitive load framework, this may lead to a contradiction when dealing with a complex learning task that includes sequences of sub-tasks. While for this complex task, the goal of acquiring domain-specific schema in long-term memory is explicitly or implicitly stated as an overall default goal that determines an optimal instructional method according to the existing cognitive load framework, the actual cognitive load, and means for its management belong to the micro-level of instruction and the corresponding level of goals. To avoid this contradiction, the specific local-level goals of learner activities should become an essential attribute of cognitive load theory (as any other instructional theory). While the acquisition of complex domain schemas could be an overall macro-level goal of complex learning tasks (even though they may have other goals), specific micro-level sub-tasks may have different goals (that together could lead to achieving the overall goal). Selecting optimal instructional methods would depend on these specific goals rather than only on the overall generic goal.

For example, when learning to solve complex physics problems, the overall macro-goal is the acquisition of the solution procedures (schemas) for these problems. However, it may involve such specific micro-goals as motivating and engaging learners, activating their prior knowledge, acquiring the specific solution schemas for the corresponding sub-tasks (e.g., applying specific conservation laws), automating the acquired schemas, or acquiring a generalized solution schema suitable for solving a broader class of problems. Optimal instructional methods (e.g., problem-solving tasks, worked examples, example–problem pairs, self-explained examples, etc.) would be determined by these specific goals at the local level rather than by the overall macro-goal.

Any complex learning task usually includes a sequence of learner activities designed to achieve corresponding specific goals, some of which could be different from the immediate acquisition of domain-specific schemas. For example, if activating and differentiating learner prior knowledge relevant to the task or enhancing learner awareness of the problem situation is such immediate goals (as suggested for initial learning phases in productive failure or invention learning approaches), they may require appropriate learner activities prior to those designed for the acquisition of the targeted schemas. According to the productive failure or invention learning approaches, exploring a problem prior to studying the explicitly provided optimal solution procedure for this problem could be an example of such activity. Therefore, the effectiveness of instructional methods needs to be viewed not only from the perspective of the generated cognitive load, but also (and firstly) within the context of specific goals to be achieved.

The Dependence of Types of Cognitive Load on Specific Goals of Learning Activities

According to the suggested conceptual framework, the type of cognitive load involved in learning activities may depend on specific goals of those activities. By traditional definition, intrinsic cognitive load is the load relevant to learning while extraneous load is irrelevant to learning. Accordingly, if an instructional method is not suitable for achieving the goal of acquiring a domain-specific schema as the only goal in a traditional cognitive load framework and would therefore be viewed as generating extraneous cognitive load from that perspective, it could still be potentially suitable for achieving a different instructional goal, and in that case, it might be considered as relevant or intrinsic (productive) cognitive load.

Thus, the same learner activities may generate intrinsic or extraneous load depending on the specific instructional goals that they are designed to achieve. It should be noted that this relativity applies to instructional goals that assume acquisition of some sort of new knowledge. Some other activities involved in learning, such as activation of prior knowledge and other activities aimed at pre-instruction goals (see the earlier section), could be categorized in a broader sense as activities aimed at achieving specific performance goals that do not directly contribute to instructional goals, but rather create some necessary conditions for them.

For example, for the goals of activating potentially relevant knowledge or enhancing learner awareness of the problem situation in the previously mentioned example with basic linear equations, the initial exploration of the problem could possibly be effective in achieving these goals. However, it is still difficult to categorize such activities as contributing to intrinsic cognitive load because problem solving itself is not directly contributing to learning new knowledge but rather prepares students for future learning, but whether they actually will do so depends on the subsequent learning activity.

On the other hand, if the goal in the linear algebra equation example is the application of the previously learned solution schema by relatively more knowledgeable learners in order to strengthen or automate the schema, solving a series of problems with simple feedback on the correctness of answers could be the activity with clear instructional goals. In this case, the application of the acquired solution rule would constitute the processes contributing to the intrinsic load. If the goal is achieving deep understanding and transfer of knowledge, prompting self-explanations of worked-out solution steps using the principles of the domain (self-explanation effect) could lead to connecting currently processed solution steps (e.g., dividing both sides of the equation by the coefficient on its left side) with the corresponding domain principles (e.g., both sides of any equation could be multiplied or divided by the same amount), accordingly changing the associated intrinsic cognitive load. Thus, the intrinsic load and cognitive activities that contribute to it depend on specific goals to be achieved.

The deleterious effects of high levels of cognitive load on the acquisition of specific domain schemas have been observed in numerous studies in cognitive load theory and are well established. However, they do not necessarily imply that similar negative effects would always apply to achieving different goals. Theoretically, it is even possible that cognitive load may not influence the effectiveness of achieving some types of goals. For example, would the abovementioned goals of activating learner prior knowledge or enhancing learner awareness of the problem situation as specific goals of corresponding activities be adversely affected by the magnitude of the experienced cognitive load? Possibly not, although there is no specific empirical evidence to answer this question confidently. However, if the results of research in the productive failure or invention learning approaches (see the following sections for more details) are viewed from this perspective, they could conceivably be considered as such evidence. Thus, an increased cognitive load experienced by novice learners during the initial exploring or solving a problem may lead to different instructional consequences depending on the specific goal of this activity. It could be unsuitable for effectively instructing these learners in specific solution schemas but might possibly be effective for activating learner prior knowledge related to the task or enhancing learner awareness of the problem situation.

In their critical analysis of basic assumptions of cognitive load theory, Schnotz and Kürschner (2007) noted the potential relativity of types of load to instructional goals, especially in relation to the discussion of the meanings of intrinsic vs extraneous load. “Learning tasks are derived from educational objectives and include therefore a normative component. Accordingly, what counts as intrinsic cognitive load depends also on educational objectives… The distinction between intrinsic and extraneous load depends (among others) on the educational objectives” (p. 478). The relativity of the types of cognitive load to the goals of learning activities was also mentioned by De Jong (2010) in his criticism of traditional cognitive load approaches to defining different types of load. For example, he suggested that “germane processes can be considered to be extraneous depending on the learning goal” (p. 111). In support of this statement, two studies were mentioned. One had been conducted by Gerjets and Scheiter (2003) who demonstrated that contrary to expectations, a deep structure-emphasizing approach (presumably generating increased productive, relevant load contributing to schema construction and abstraction processes) was inferior to a surface-emphasizing approach in achieving the goal of enhancing students’ abilities to solve isomorphic problems. Accordingly, the expected relevant processes were judged as extraneous, irrelevant activities to this goal. Another study had been conducted by Scott and Schwartz (2007) who concluded that the use of navigational maps in learning from hypertext-based instruction could be regarded as generating either productive (relevant) or extraneous load depending on whether the goal of this activity is understanding or navigation.

The Expertise Reversal Effect and Instructional Goals

As was mentioned previously, explicit instruction with comprehensive guidance that describes all the details of required steps to learners is strongly supported by cognitive load theory (the worked example effect) and contrasted with the instructional approaches advocating reduced or minimal levels of guidance (Sweller et al. 2011). It should be noted that these opposing views on the degree of required instructional guidance concern only novice or low prior knowledge students. For more knowledgeable students ("experts" in the specific classes of learning tasks), cognitive load theory also advocates the use of reduced or minimal guidance according to the expertise reversal effect (Kalyuga 2007; Kalyuga et al. 2003; Sweller et al. 2011). This effect refers to stable patterns of interactions between levels of learner prior knowledge (expertise) and effectiveness of alternative instructional techniques. According to one of such established patterns, for novice learners, especially during the initial stages of skill acquisition, comprehensive forms of explicit guidance facilitate learning domain-specific schemas. On the other side, for more advanced and knowledgeable learners and during later phases of skill acquisition, various forms of reduced or minimal guidance (such as problem-solving or exploring tasks) could be more effective than explicit guidance. For example, in the context of learning from example–problem or problem–example sequences, based on the expertise reversal effect, the recommendations have been quite similar to those suggested by alternative frameworks advocating reduced levels of guidance. Reisslein et al. (2006) demonstrated the superiority of problem–example sequences for high prior knowledge participants on near-transfer post-tests.

Thus, the expertise reversal effect deals with the relative effectiveness of alternative instructional methods for learners with different levels of expertise. If, in addition to levels of learner expertise, instructional goals also determine the effectiveness of instructional methods, then these goals need to be considered when selecting instructional approaches for learners with different levels of expertise. In particular, instructional methods could be meaningfully compared for learners with different levels of expertise only if these methods are used for achieving the same goal. From this point of view, the expertise reversal effect should imply the suitability of an instructional method for achieving a specific goal by the learners with a specific level of expertise. When analyzing empirical evidence related to the expertise reversal effect, it is necessary to establish instructional methods that are effective for achieving specific goals by learners with different levels of expertise in a domain.

For example, comparing the example–problem and problem–example sequences for learners with different levels of expertise may not be an appropriate experimental design if studying examples and solving problems are intended for achieving different goals. The inclusion of problem-solving activities in these two types of sequences could be driven by very different specific goals. According to cognitive load theory, in the example–problem instruction, the goal of problem-solving phase is to apply and reinforce the solution schema learned from the preceding worked example. On the other hand, in the problem–example instruction according to the productive failure approach, the goal of the problem-solving phase is activating and differentiating learner prior knowledge (or enhancing learner awareness of the problem situation, from another perspective) prior to the following explicit instruction in the solution schema.

Thus, the expertise reversal effect should be investigated and applied within the context of the same goals. For example, according to this effect, if could be expected that if minimally guided learning tasks prior to explicit instruction might be potentially effective with novice learners for achieving some of the above-mentioned pre-instruction goals (e.g., activating relevant prior knowledge or enhancing awareness of the situation), they might not be suitable for achieving these goals with more knowledgeable learners. The same applies to higher-order goals such as those related to the acquisition of deep structures (principles) of a domain. Explicit forms of instructional guidance highlighting the deep structure of the problems and knowledge of higher-level generality (e.g., Kalyuga et al. 2010) could be experimentally compared with relatively less guided generation or exploration activities at different levels of learner expertise (assuming the higher-order instructional goal remains the same).

The major instructional implication of the expertise reversal effect in the traditional description of cognitive load theory is that instructional procedures (by default, all aimed at the acquisition of domain-specific schemas) should be tailored to levels of learner prior knowledge or expertise. Accordingly, smooth transitions are required from comprehensively guided explicit instruction during early phases of learning a specific task domain to reduced levels of guidance as learners acquire more knowledge and, finally, to unguided forms of instruction as they acquire sufficient levels of proficiency in the domain. Such transitions could be implemented in the form of example–problem pairs (Cooper and Sweller 1987), completion tasks that provide partially worked out solutions first and, then, learners are asked to complete the solution (Van Merriënboer 1990; Van Merrienboer et al. 2003), or faded worked examples based on linking a sequence of completion tasks with progressively reduced levels of instructional guidance (Atkinson et al. 2000; Renkl 1997; Renkl and Atkinson 2003). The faded guidance approach is based on the assumption that the progressively (rather than abruptly) reduced levels of instructional support with increased levels of learner knowledge would always leave sufficient cognitive resources for coping with the increased demands of independent problem solving (Sweller et al. 2011). The most advanced form of integration of different degrees of guidance considered in cognitive load theory is using adaptive fading approaches that allow dynamic tailoring of instructional support to increasing learner proficiency levels (e.g., Kalyuga 2006; Salden et al. 2006; Salden et al. 2010).

However, all the above approaches generated within a traditional cognitive load perspective assumed acquisition of corresponding domain-specific schemas as a unitary instructional goal. The introduction of differentiated goals may require appropriate modifications to the adaptation methodologies used in these approaches. As was mentioned previously, the need to consider different goals at different phases of cognitive skill acquisition was discussed by Renkl and Atkinson (2003) and Renkl (2014) who suggested that such differences in goals determined what should be presented to the learners according to the guidance fading procedure.

Abandoning the Explicit Instruction–Limited Guidance Dilemma in Complex Learning

In cognitive load theory, which promotes increased levels of explicit instructional guidance, especially for novice learners, the exploratory, inquiry, or problem-based learning environments have been traditionally considered in the category of instructional approaches advocating reduced or minimal levels of guidance. These two positions (explicit vs. minimal guidance) are often viewed as representing the opposing extremes in the degree of instructional guidance provided to learners, and there has been a long history of debates between supporters of these views (e.g., see Hmelo-Silver et al. 2007; Kirschner et al. 2006; Klahr 2009; Kuhn 2007; Mayer 2004; Schmidt et al. 2007 for some recent examples).

From a traditional cognitive load perspective, all the alternative to explicit guidance approaches have been uniformly viewed as also aimed at the acquisition of domain-specific schemas similar to any instructional task considered in this theory. However, complex learning environments—such as those implementing problem-based learning or inquiry learning—usually involve various learner activities with different specific goals. The instructional methods that could be used for achieving these goals may involve various forms and levels of instructional support for learner problem-solving or exploratory activities (e.g., De Jong 2005; Alfieri et al. 2011; Hmelo-Silver et al. 2007; Lorch et al. 2010; Mayer 2004). They may include explicit comprehensive guidance, partial support, or minimal assistance (e.g., hints or simple feedback). In such learning environments, instructional methods with different levels of guidance aimed at achieving corresponding goals would inevitably be intermixed. Explicit comprehensive forms of guidance could co-exist with reduced or minimal levels of guidance. Therefore, the traditional duality of explicit instruction and limited-guidance instruction could not be warranted in a complex multi-goal learning environment as a whole. This distinction could only be meaningful at the local level of activities used for achieving specific goals. As mentioned previously, this is also the level at which cognitive load phenomena should be primarily approached. The presence of various levels of instructional guidance in complex learning environments is evident when they are analyzed at this level.

For example, in problem-based learning, students formulate learning issues that they then need to answer by studying various literature sources; it usually includes presenting a problem scenario, initial discussion, self-study, and reporting (Schmidt et al. 2007; Wijnia et al. 2014). Problem-based learning is rather flexible in sequencing specific goals and could therefore flexibly adapt different levels of instructional guidance. For instance, any missing prerequisite knowledge not activated during the initial discussion (Schmidt et al. 2009) is usually provided explicitly by the teacher. When providing resources for individual studies with the goal of acquiring domain-specific knowledge, novice learners are usually given a restricted set of resources to reduce irrelevant search activities, and then, the restriction is gradually removed as learners acquire more knowledge. Also, the required content knowledge is often provided by instructors on a just-in-time basis as explanations (comprehensive explicit guidance) or feedback (partial guidance).

Complex problem-based and inquiry learning environments usually involve a mixture of various instructional methods with differing levels of instructional support (Schmidt et al. 2009). They use relatively less explicit comprehensive forms of guidance (normally provided on a just-in-time basis) but involve plenty of distributed throughout the learning environment instructional scaffolding and other forms of partial guidance suitable for achieving specific goals (Hmelo-Silver 2004; Hmelo-Silver et al. 2007; Schmidt et al. 2007, 2009; Schwartz and Bransford 1998). Well-designed inquiry learning environments—the environments that engage students in formulating questions, problems, or scenarios and then conducting investigations to find answers and thus build their knowledge—are also heavily scaffolded at each step of the inquiry process with progressively reduced levels of support as the students become more skilful in the process (White 1993; White and Frederiksen 1998). The level of detail, types of prompts, and other support means that are essential for achieving specific goals are tailored to learner prior experience and content knowledge.

Thus, complex problem-based and inquiry learning environments involve various levels of instructional support from full, comprehensive guidance to different forms of partial and minimal guidance depending on specific goals at different phases of the learning process. Still, in cognitive load theory, such learning environments are traditionally considered as minimally guided instruction overall. If specific goals at local, micro-levels of instruction are incorporated in the revised cognitive load framework, its recommendations or effects (methods) should rather not be applied to a complex, multi-goal learning environment as a whole but should be applicable only to its individual phases or activities directed to achieving specific goals, in this case—to acquisition of domain-specific concepts and procedures.

Alternative Views on the Role of Initial Generation Activities in Instructing Novice Learners

Some theoretical frameworks on the minimal-guidance side of the asserted direct instruction vs minimal guidance dichotomy—such as productive failure (Kapur 2008, 2011), invention activity to prepare for future learning (Schwartz and Bransford 1998; Schwartz et al. 2011; Schwartz et al. 2009; Schwartz and Martin 2004), or "desirable difficulties" (Schmidt and Bjork 1992)—suggest that using exploratory or problem-solving activities prior to explicit instruction would result in deeper learning from the following instruction. The initial phase of instruction (called the generation or invention phase in the above approaches) during which students attempt to solve—usually unsuccessfully—the intended problem on their own or with some limited assistance could include different activities. For example, Kapur (2010; 2011; 2012) asked students to solve complex novel problems collaboratively in small groups (most were unsuccessful) and, then, at the second phase, explicitly explained the standard solution and compared it with students' solutions. The results indicated that on post-tests, students in the productive failure conditions outperformed those in the alternative condition (who started from the direct instruction that provided standard solution and later solved similar post-instruction practice problems) on conceptual understanding and transfer, with the same level of performance on retention tests (though it should be noted that the validity of those results has been questioned in cognitive load theory based on non-equivalence of the compared experimental conditions, e.g., Hsu et al. 2015; see also Glogger-Frey et al. 2015 for a discussion of the issue of control groups in productive failure/inventing studies).

Similar results were reported by Kapur and Bielaczyc (2012); however, in a follow-up experiment, they also demonstrated that the students who generated the solutions themselves prior to explicit instruction on the standard solution outperformed the students who studied the explicitly described student-generated solutions as worked-out examples prior to explicit instruction on the standard solutions, on conceptual understanding, and near transfer tests with no differences on retention (procedural fluency) and data analysis tests. Because it was suggested that the purpose of the generation phase was to create conditions in which students would attend to critical features of possible solutions, the most strong direct-instruction alternative to be compared with should provide these critical features explicitly prior to the direct instruction in standard solution. Such condition was used in the final experiment of Kapur and Bielaczyc (2012), and students in the productive failure condition still outperformed this “strong” explicit instruction-only condition group on the test of deep conceptual understanding with the same level of performance on procedural fluency and near transfer tests.

The purpose of the generation or initial exploration phase has been interpreted differently. According to Bransford and Schwartz (1999), the initial inventing activity would allow students to better understand deep structures behind the expert solutions explained later explicitly. It is argued that if such solutions are explicitly provided from the beginning, they would focus learner attention on specific procedures and their applications rather than on deep structures behind the solutions. Another often indicated purpose of the generation or exploration phase is to activate and differentiate any available learner prior knowledge and ideas (such as intuitive knowledge) potentially related to the conceptual knowledge to be learned (Kapur 2010; Kapur and Bielaczyc 2012; Kapur and Rummel 2012; Schwartz and Martin 2004). For example, Kapur (2012) and Kapur and Bielaczyc (2012) reported that in the productive failure condition, the diversity of the solutions generated by students significantly correlated with learning outcomes. Loibl and Rummel (2014) suggested enhancing a global awareness of knowledge gaps (awareness without being able to identify specific missing components) as the major role of a problem-solving phase prior to explicit instruction.

From a cognitive load perspective, novice learners who have to solve or explore a novel problem would likely experience a heavy cognitive load which should inhibit rather than enhance learning, contrary to what has apparently been observed in the above productive failure or invention learning studies. Kapur and Bielaczyc (2012) suggested that the activation of relevant prior knowledge during the generation phase as well as the generated potential solution procedures that become incorporated into long-term memory could possibly reduce cognitive load during the following direct instruction in new concepts (in comparison with direct instruction without a preliminary activation of prior knowledge). However, realistically, in order to reduce cognitive load sufficiently (e.g., based on chunking or encapsulation of information into larger units or according to the long-term working memory mechanism suggested by Ericsson and Kintsch 1995), the available knowledge should represent well-learned and stable structures or schemas in long-term memory rather than some of their activated components, vague intuitive ideas, or just partial schemas under development. Therefore, this explanation does not look quite viable from a cognitive load perspective.

Considering these instructional approaches within the context of potentially variable goals of specific learning activities may offer a more plausible explanation. The generation or exploration phase in the productive failure and invention learning approaches is apparently not aimed at the acquisition of the corresponding solution schema (which is explicitly provided in the following phase). As mentioned previously in this paper, some of the suggested goals of the generation phase were activating and differentiating learner prior knowledge, enhancing learner awareness of the problem situation, focusing learner attention on deep structures behind the solutions rather than on specific procedures and their applications, or enhancing a global awareness of knowledge gaps. These goals could possibly be optimally achieved by approaches that might differ from explicit instruction which is most effective (from a cognitive load perspective) for the acquisition of domain-specific solution schemas by novice learners. The suggested reconciliation of productive failure and invention learning approaches with worked example effect in cognitive load theory is, in principle, similar to the way of reconciling the differences between the testing effect and worked example effect based on the Knowledge–Learning–Instruction (KLI) framework: the choice of optimal instructional method depends on the specific knowledge acquisition goal (Koedinger and McLaughlin 2014).

Therefore, the reported cases demonstrating the effectiveness of using the initial generation phase in productive failure and invention learning approaches may not actually contradict cognitive load theory, as the specific goals of this phase are different from the instructional goals considered in cognitive load theory—i.e., the acquisition of domain-specific knowledge structures (schemas). The specific goals of the generation phase (e.g., activating and differentiating prior knowledge, enhancing awareness of the problem situation or knowledge gaps) could be helpful and important (or possibly even essential in some situations) for the following in the next phase acquisition of domain-specific knowledge with certain characteristics (e.g., the degree of transferability, flexibility, applicability, and duration). Besides, the increased levels of cognitive load that learners may experience during the generation phase might not necessarily negatively affect achieving the specific goals of this phase.

For example, the initial discussion in complex problem-based learning and the initial problem exploration in the productive failure approaches are not considered as immediate means of acquisition of solution schemas for the corresponding problems. Therefore, the cognitive load generated by such activities may not be irrelevant to the intended goals of these activities. If still present, any irrelevant to the intended goals parts of it could possibly be reduced using established cognitive load techniques such as preventing split attention, eliminating redundant information, using signaling means, providing comprehensive or partial guidance, etc. It should be noted that the goals usually associated with the generation phase preceding explicit instruction in the productive failure or invention learning approaches (e.g., pre-instruction goals or the goals of acquisition of generalized domain knowledge) belong to the levels of goals different from the level of acquisition of domain-specific schemas in the taxonomy of goals suggested earlier in this paper.

Glogger-Frey et al. (2015) also indicated a possibility of several different goals for the generation phase in invention learning or productive failure approaches to co-exist more or less "simultaneously"—e.g., by contributing to activating prior knowledge, constructing skeletal prior knowledge, focusing on deep structure, making learners aware of their knowledge gaps, eliciting curiosity or interest, etc. In this situation, there might also be potential cases in which the demand of the corresponding generating activities could be productive for certain goals and unproductive for other goals. This issue should be further investigated in line with the previously mentioned need to develop a better hierarchy and sequences of instructional goals for different parts of complex learning environments.

Thus, in the case of contrasting the productive failure phenomenon with worked example effect, the initial problem-solving or exploratory activities (as minimal- or reduced-guidance forms of instruction) would generate unproductive, extraneous load when used for instructing learners in specific solution schemas, but not when used for achieving some other goals (e.g., activating learner prior knowledge and intuitions or enhancing learner awareness of the problem situation, according to the corresponding theoretical frameworks). Besides, since such goals are not related to the acquisition of domain-specific schemas, the magnitude of this load may potentially not affect achieving some of these goals even if it exceeds available working memory resources. The principle of cognitive load theory according to which overloading working memory is harmful for learning (meaning learning domain-specific schemas) may not be applicable to this situation.

It should be reiterated that in many situations, various instructional methods could be meaningfully compared only if they are used for achieving the same set of intended goals (unless different sets of instructional methods are compared to demonstrate that different goals could be achieved with some of these in order to argue for the greater effectiveness of the corresponding approaches—in such cases, a set of dependent variables should take the sub-goals of the to-be-compared methods into account). For example, comparing the example–problem and problem–example sequences in order to contrast the explicit fully guided instruction (supported by the worked example effect in cognitive load theory and provided by example–problem pairs) with productive failure or invention learning approaches (that argue for placing problem-solving experiences before the explicit instruction) may not be the best experimental design. The inclusion of problem-solving activities in these two approaches is driven by very different intended specific goals. In the example–problem instruction according to cognitive load theory, the goal of problem-solving phase is to apply and reinforce the solution schema learned from the preceding worked example. In the problem–example instruction according to the productive failure approach, the intended possible goal of the problem-solving phase is activating and differentiating learner prior knowledge or enhancing learner awareness of the problem situation or own knowledge gaps prior to the following explicit instruction in the solution schema (see above for different suggestions in this respect).

When designing experiments for investigating the effectiveness of productive failure/invention learning approaches in comparison with explicit instruction, the generation (or its equivalent) phase of the productive failure approach should be experimentally manipulated with the second phase (explicit instruction only or explicit instruction followed by a problem-solving practice) kept identical for all the compared experimental conditions. If the assumed goal of the first phase is activating learner prior knowledge, then different possible means for achieving this goal in the first phase—such as unguided problem solving/exploring, problem solving/exploring with some forms of partial guidance, or explicit instruction means of knowledge activation (a strong explicit instruction alternative)—should be compared with no-knowledge-activation condition as a control condition (see Glogger-Frey et al. 2015 for further discussion of this issue).

For investigating potential expertise reversal effects for productive failure approach vs explicit instruction, learners with different levels of expertise should be used with both approaches. If the effectiveness of minimally guided instruction for achieving the above goal with novice learners has been allegedly established (e.g., Kapur and Bielaczyc 2012; Kapur 2014), the comparisons of such alternative methods with more knowledgeable learners have not been done. These learners may benefit neither from the minimally guided activities nor from any other alternatives aimed at activating their prior knowledge (with the control condition possibly emerging as the most effective one). The optimal levels of embedded guidance during the exploration activities that occur prior to explicit instruction should also be investigated (Lee and Anderson 2013). For example, forms of metacognitive support (metacognitive scaffolding) using questions and prompts during the generation phase could be an effective form of partial support (Roll et al. 2012) for achieving the intended specific goals of this phase. The alternative forms of embedded partial guidance should be investigated using learners with different levels of prior knowledge (to uncover a possible expertise reversal effect).

Conclusion

This paper intended to reconsider some of the traditional approaches in cognitive load theory without changing its most fundamental assumptions. This is necessary in order for the theory to be able to assimilate some of the emerging contradictory empirical evidence and better define its boundaries and areas of applicability. The suggested modifications could be briefly summarized in the following statements.

The concepts of information element and element interactivity have been important for describing basic mechanisms and definitions in cognitive load theory. However, theoretically, they are limited in their ability to include and explain the whole variety of cognitive events and processes contributing to cognitive load in complex learning. The concept of cognitive activity as comprising all processes and operations involved in achieving a specific goal may be useful in describing cognitive load phenomena (with element interactivity considered as its practically usable approximation). The cognitive load generated by a learning task as the measure of required working memory resources could then be defined as the intensity of cognitive activity involved in achieving a specific goal of the task.

The specific goals of learner activities need to be treated as essential attributes of the theory. While the traditionally described generic, uniform goal of acquiring domain-specific schemas is indeed a major goal of instruction, various instructional stages and tasks may have different specific goals. Accordingly, the suitability of a particular instructional method or technique depends on its relevance to achieving a specific goal.

In relation to the type of cognitive load (intrinsic vs extraneous) generated by an instructional method, it is also determined by the relevance of this method to achieving a specific instructional goal. From this perspective, some instructional methods that may not be suitable for achieving the goal of schema acquisition, and therefore traditionally classified as causing extraneous cognitive load, may be effective in achieving different instructional goals and accordingly associated with intrinsic cognitive load.

When deciding on the effective instructional methods for learners with different levels of expertise (according to the expertise reversal effect), specific instructional goals need to be taken into account. Different instructional methods can be directly compared if they are used for achieving the same set of specific goals. Therefore, the expertise reversal research should be aimed at establishing effective instructional methods for achieving specific goals by learners with different levels of prior knowledge in a domain. In particular, fully guided explicit instruction (e.g., worked examples) and less guided instructional methods (e.g., based on exploratory and problem-solving activities) could be compared for learners with different levels of expertise if they are intended for reaching the same set of specific goals.

When dealing with complex (multi-task and multi-goal) learning environments, cognitive load should be treated as a local, micro-level phenomenon that varies on the timescale of working memory operation and is associated with cognitive processes within a limited time range of cognitive activities aimed at achieving specific goals rather than a global, macro-level phenomenon over more prolonged periods of time and larger instructional units. Accordingly, managing cognitive load should be treated as the micro-management task on a local scale rather than the macro-management on a larger scale.

Since complex learning associated with problem-based and inquiry learning environments includes various cognitive activities with different specific goals, the instructional methods suitable for achieving those various goals could involve different levels of instructional support even for the learners at the same level of expertise. Therefore, various instructional methods with different levels of instructional guidance could be intermixed at local levels within a complex learning task. Accordingly, the traditional dichotomy of explicit fully guided instruction and reduced-guidance methods may need to be abandoned and replaced by a more flexible approach based on differentiating instructional goals of specific activities involved in complex learning.

Some of the empirical results that might be accommodated as not contradicting cognitive load theory due to this modification of the conceptual framework are the results of studies within the frameworks of productive failure and invention learning According to the traditional view of cognitive load theory, novice learners benefit most from fully guided explicit instruction (the worked example effect), while more knowledgeable learners may learn most effectively from instructional materials with reduced or minimal levels of instructional support. However, studies within the above alternative frameworks seemingly oppose this view by demonstrating that minimally guided learning tasks provided prior to explicit instruction could be more effective for achieving better and longer-lasting learning outcomes with novice learners than providing explicit instruction first. Since the stated goals of such initial problem-solving or exploring tasks are different from the immediate acquisition of domain-specific schemas, such results do not contradict the reconceptualized cognitive load framework.

Thus, it could be predicted that cognitive load effects (showing the benefits of the corresponding instructional methods), including the worked example effect as one of the best known and most tested effects consistent with this theory, might not be observed in situations in which the corresponding learner cognitive activities are used for achieving specific goals that are different from the goal of acquisition of domain-specific schemas. Accordingly, any empirical evidence in favor of fully guided explicit instruction or less guided learning environments needs to be treated within the context of specific goals in specific situations for specific types of learners. The selection of optimal instructional methods should be based on their empirically established effectiveness in achieving specific goals by learners with particular cognitive characteristics. In future research, it is important to determine a sequence of instructional sub-goals that are pursued in certain instructional approaches. Making the sub-goals explicit is an important prerequisite for choosing productive learning activities in different phases of instruction. The continuing research within a modified cognitive load framework could provide valuable guidance in this process.

Finally, some comments need to be provided in relation to the big picture in the foundation of cognitive load theory. Sweller (2003; see also Sweller et al. 2011) suggested an evolutionary perspective on human cognitive architecture by considering it as an example of a more general class of natural information processing systems. By comparing the operation of human cognition with the evolution by natural selection as a biological system—both representing natural information processing systems—he formulated a set of general principles that are presumably common to all such systems. One of these principles is the borrowing and reorganizing principle according to which most of information stored in natural information processing systems is borrowed from other stores (in the case of human cognition, from other people) rather than generated anew. It is suggested that this principle underpins the worked example effect in cognitive load theory. Indeed, this is the most efficient way of acquiring new domain schemas, if schema acquisition is the goal of the learning task. In other natural information processing systems (e.g., biological systems or possibly even non-organic systems, see Kalyuga 2015 for some speculations in this respect), transmitting and acquiring stable information patterns are possibly the only form of "learning" for which such systems are naturally predisposed or internally "motivated."

In human cognition (in which stable information patterns are essentially represented by schemas of various types), this natural learning ability relates to the acquisition of what Geary (2007) calls biologically primary knowledge. We are apparently evolved to be genetically predisposed to acquire such evolutionary essential schemas or information patterns in a rapid and implicit way (e.g., skills in speaking and listening basic native language). However, we have not evolved to be predisposed to acquire in this way biologically secondary knowledge such as scientific knowledge or abilities to write and read, and therefore, we are not naturally motivated to learn such knowledge. As a consequence, the processes of learning the corresponding biologically secondary information patterns (schemas) in human cognition may require additional learning activities that are not present or even required in other natural information processing systems—such as activities aimed at motivating or engaging the learners in the processes of acquisition of the above schemas or activating their relevant prior schemas. Accordingly, the above borrowing and reorganizing principle (interpreted as the worked example effect in human cognition) may not directly extend to such activities.

Thus, in general—on the level of its basic, fundamental characteristics—human cognition apparently follows the general principles of natural information processing systems when it concerns transmitting or acquiring stable information patterns (schemas) as the universal form of learning in the natural world. However, human cognition has seemingly evolved to be more complex than most other natural systems and, therefore, may require additional forms of learning activities with goals different from the immediate acquisition of domain-specific schemas (or in general—stable information patterns). Such activities and the corresponding goals have been considered in this paper as attributes that need to be included in a modified framework of cognitive load theory in order to better understand its boundaries.

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