Cognitive Load Theory for the Design of Medical Simulations

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Summary Statement: Simulation-based education (SBE) has emerged as an effective and important tool for medical educators, but research about how to optimize training with simulators is in its infancy. It is often difficult to generalize results from experiments on instructional design issues in simulation because of the heterogeneity of learner groups, teaching methods, and rapidly changing technologies. We have found that cognitive load theory is highly relevant to teaching in the simulation laboratory and a useful conceptual framework to reference when designing or researching simulation-based education. Herein, we briefly describe cognitive load theory, its grounding in our current understanding of cognitive architecture, and the evidence supporting it. We focus our discussion on a few well-established cognitive load effects with examples from simulation training and recommend some instructional applications with theoretical potential to improve learning outcomes.
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Cognitive load theory (CLT) should be considered a key instructional theory for medical educators because of its strong evidence base and its relevance to our understanding of human cognitive architecture. This theory is founded on the fact that working memory has a limited capacity when dealing with novel information and, when requirements surpass this capacity, then learning is impaired.[1] Initially, much of the enthusiasm for healthcare simulation was related to its grounding in adult learning theory and, in particular, Kolb's cycle of experiential learning.[2] It is now well established that simulation-based training techniques are effective[3] and the research agenda has shifted to one of how to best apply this educational technique. With this shift, CLT is being increasingly cited as another important theoretical framework[3–5] and we feel that a discussion of the origins of CLT, emerging evidence, and its limitations is timely for both researchers and educators. In this review, we use examples from immersive simulations (see Table 1 for definition) wherever possible because these complex learning environments place a high demand on the cognitive resources of the learners and CLT is most relevant in this context. However, the principles of CLT are also important to those using standardized patients (SPs), task trainers, and other simulators because the cognitive architecture of all learners is limited by a finite working memory capacity. Most of the data available to support the theory come from experiments in high school and college learners in traditional learning environments,[8–10] as well as trade apprentices in the work place,[11] so we strongly advocate for the repetition of empirical CLT studies in the simulation context. In the interim, our recommendations for healthcare simulations are generalizations and predictions derived from the available evidence supporting this influential learning theory.

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COGNITIVE LOAD THEORY

Cognitive load theory[1] is used to devise instructional procedures based on our knowledge of human cognitive architecture. Cognitive load theory differs from many other educational theories in that it emphasizes explicit rather than minimal guidance during instruction[12] and assumes that the knowledge acquired in academic areas such as medicine is domain specific rather than generic.[13] Foundational to this theory is the fact that working memory has a limited capacity and duration when dealing with novel information. When the capacity or duration of working memory is surpassed, learning is impaired.[14] In contrast, working memory has no known limits when dealing with previously organized information that is retrieved from long-term memory. Immensely complex bodies of information can be dealt with by working memory providing it first has been organized and stored in long-term memory. Accordingly, expertise and skill derive from the storage of immeasurable amounts of domain-specific knowledge in long-term memory.[15] It follows that the function of instruction is to build the large knowledge bases in long-term memory required for skilled performance.

Evidence for the size and influence of long-term memory in activities such as problem solving comes from pioneering research using the game of chess. In his classic work, De Groot[16] found that the only difference between chess masters and weekend players was in memory of chess

TABLE 1. Glossary of Terms

Instructional design	Prescriptions for teaching methods to improve the quality of instruction with a goal of optimizing learning outcomes.
Working memory	A theoretical model of the cognitive system that provides temporary storage and manipulation of information necessary for complex tasks.[6] Working memory deals with all conscious processing but is extremely limited in capacity (can hold 7 ± 2 items) and duration (seconds). Working memory is thought to consist of 2 "short-term memory" storage systems: an auditory processor, a visual processor.
Short-term memory	Short-term memory as a concept generally refers only to storage of information, without considering processing and organization.
Long-term memory	The storage of immense amounts of information in the form of complex schemata, which can be accessed by working memory as a single element. Long-term memory has no known limits to capacity or duration.
Cognitive Load Theory (CLT)	A theory of instructional design based on our knowledge of human cognitive architecture.[1]
Intrinsic cognitive load	The demands on working memory caused by the intrinsic nature of the learning task, especially related to element interactivity.
Extraneous cognitive load	Demands on working memory caused solely by the format of instruction rather than the nature of the information to be learned.[1]
Germane cognitive load	Working memory resources required to process intrinsic load.[1] Germane load is typically increased by altering the nature of the task to encourage deeper processing and construction of well-connected schemas.
Achievement/academic emotions	Emotions that are directly linked to learning, instruction, and/or performance, for example, motivation to learn and performance anxiety.[7]

board configurations taken from real games. When shown a board configuration taken from a real game for 5 seconds, masters could reproduce the board with approximately 80% accuracy whereas weekend players had an accuracy rate of approximately 30%. Both weekend players and masters had an accuracy of approximately 30% for random board configurations.[17] The implication is that chess grand masters win their games because they have learned to recognize tens of thousands of board configurations along with the best moves for each configuration. Expert decisions concerning chess moves depend on previous knowledge just as expertise in medicine relies on huge amounts of domain-specific information stored in long-term memory.[15] An experienced emergency department practitioner can analyze an arterial blood gas and rapidly recognize acute respiratory acidosis because they have previously spent many hours training on the individual components of the task including the basic science of acid-base balance, gas exchange principles, and common presentations of respiratory diseases.

Based on this cognitive architecture, the function of instruction is to change the content of long-term memory so that working memory can ultimately use stored information for activities that otherwise would be impossible. However, instruction generally occurs before information being transferred to long-term memory, and so, to be effective, instruction must consider the limitations of working memory when dealing with novel information. The working memory load imposed by instruction consists of the intrinsic complexity of the material, called *intrinsic cognitive load*, plus the nature of the instruction, that can lead to *extraneous cognitive load*. Extraneous load is defined as working memory resources required for task completion that do not enhance learning and may be due to poor instructional design. Instructional design that engages learners in processing directed to the construction of schemas is termed *germane load*, a subtype of intrinsic load. The key concept is that if total cognitive load exceeds working memory capacity, then learning is impaired.

The effect of cognitive load on learning is not linear, and the challenge for all educators is to provide instruction that is adequately stimulating and motivating for learners without pushing them off the far end of the curve as depicted in Figure 1. This figure is taken from an experiment in which the perceived cognitive load of first year medical students after simulation training and debriefing was plotted against performance outcomes.[4] Those students with "very high" loads performed less well on subsequent testing compared with their colleagues who did not rate such high loads. Of course, the exact point at which working memory becomes overloaded is multifactorial, individual, and known to neither the student nor the instructor. Nonetheless, it is generally agreed that intrinsic cognitive load should be appropriate to the level of the learner, extraneous cognitive load should be reduced, and germane load increased so long as the limits of working memory are not surpassed.

Readers of this journal will recognize similarities between CLT and constructs discussed in related disciplines such as human factors, cognitive engineering, and decision-making sciences. Each of these fields also acknowledges the limitations of human working memory during the development of complex technological systems or work environments. Thus, the concepts discussed in this paper are not just important to those who educate using simulation techniques but also for those who use simulation to optimize the complex healthcare systems in which humans must perform.

Measuring Cognitive Load

Finding a reliable measure of cognitive load has been of great interest to CLT researchers and more recently to simulation educators.[18] To date, the most commonly used measure has been the 9-point Likert scale developed by Paas[19] with which he originally asked high school students to rate their mental effort during learning. He found that for instructional materials designed to reduce cognitive load, participants rated their perceived mental effort lower than on materials with no strategy to reduce cognitive load. The self-rating instrument was able to detect differences in effort required for different strategies. In this case and many studies that followed,[20] lower cognitive load corresponded to higher test performance. However, it should be noted that too little effort can also lower learning outcomes[21] indicating that this relationship is not linear.

When compared with other methodologies, Paas and van Merriënboer[22] reported that the self-rating scale was more sensitive than a physiologic measure (spectral analysis

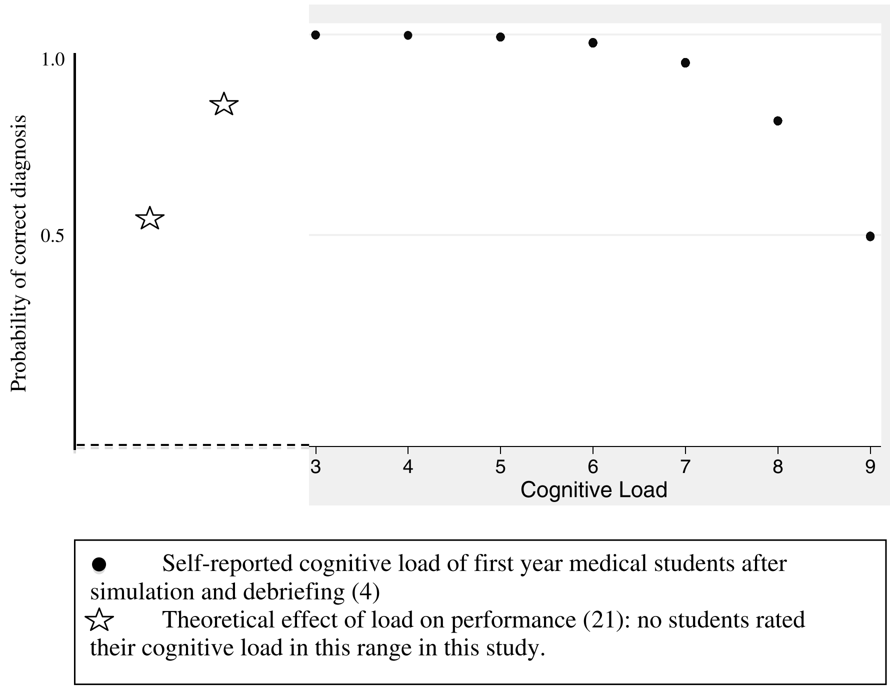

FIGURE 1. The relationship between cognitive load and learning outcomes.

of heart rate) and far less intrusive. Since then, the 1-item self-rating scale has proven to be highly reliable and able to differentiate the cognitive load imposed by different instructional procedures and task complexities.[20,23] Some CLT researchers[24,25] have developed multi-item scales to try to measure the different categories of cognitive load (intrinsic, extraneous, and germane), and the very recent work of Leppink et al[26] suggest that learners can indeed reflect on the cognitive load associated with task complexity, instructional design, and their own learning efforts, if not individual loads per se. That novel multi-item subjective instrument holds potential for future research in the area of instructional design.

Researchers in psychology have long used dual-task methodologies in which the learner's ability to react to an secondary (usually unrelated) stimulus or task, while simultaneously responding to a primary task (learning the content), is used to estimate working memory load. This technique has been found to be useful by CLT researchers particularly when instructing with multimedia materials.[27,28] Rojas et al[29] recently assessed the cognitive load of medical learners while performing a psychomotor primary task (knot tying) by asking them to respond to a predetermined change in the patient's heart rate by pressing a foot pedal. They were able to differentiate between novices and experts using response times and error rates, in addition to the subjective ratings (Paas scale). Of particular note was the investigator's novel use of a clinically relevant stimulus as the secondary task because this begins to address one of the major concerns about using dual task methodology that the secondary task will itself interfere in the learning outcome of interest.

Researchers have also advocated the use of continuous and instantaneous measures of cognitive load during a task because subjective measures can only indicate load retrospectively, after a task has been completed. Antonenko and Niederhauser[30] recently found that electroencephalogram (EEG) measures were more sensitive than a subjective measure, whereas Van Gerven et al[31] found that pupil dilation increased with higher levels of memory load. Commentators have also advocated using techniques such as functional magnetic resonance imaging[32] and eye tracking,[33] but these research areas are in their infancy and applications to the physically active learning environments in healthcare simulation will be challenging. Simulation researchers have also measured salivary cortisol[34] and heart rate variability as markers of stress, but the complex relationship between stress and cognitive load is not completely understood (see later); further research into the best physiologic markers for each is needed.

In summary, several methods have been used to measure cognitive load, although Paas' subjective scale of mental effort has had the most use and is currently the easiest to measure in the setting of simulation training. The increasing use of physiologic methods to obtain instantaneous and continuous readings, particularly during task training, is promising for future study of the complex simulation environment where we would like to understand the temporal changes in load occurring across key stages of training (briefing, scenario performance, and debriefing). Ideally, we need to measure cognitive load in addition to learning outcomes in response to manipulations of instructional design if we hope to understand the true value of CLT for designing simulation training.

SOME COGNITIVE LOAD PRINCIPLES RELEVANT TO SIMULATION DESIGN

Cognitive load theory has been used to generate a range of cognitive load principles (CLT refers to these as "effects")

TABLE 2. Some Cognitive Load Principles and Instructional Design Recommendations

Stage of Simulation Training	Strategies for Managing Cognitive Load	Practical Applications to Simulation Instruction	Related Theories or Frameworks
All	Consider the expertise reversal effect	During a scenario in which a young child with shock needs prompt assessment and resuscitation, should the accompanying parent be in the room? For novices, this could add an emotional load and perhaps impair their ability to learn about diagnosing and treating shock. Alternatively, for a more senior pediatric resident, dealing with an upset parent might be a skill that has been previously practiced (has a schema for this) and failure to present the first-hand historical source could increase mental effort if he wonders about the validity of the second hand information.	
Prerequisite knowledge	Segmentation and Pretraining	Provide prereading materials regarding the medical content to be covered. Consider revealing the case "diagnosis" before the simulation for some learners.	Sequencing[36]
		Facilitate learner access to the simulation laboratory for independent familiarization with mannequin features and environment.	Cognitive apprenticeship model[37]
		Practice on task trainers first before incorporating into simulation scenario.	
Briefing	Pretraining	Briefings should be routine and similar between sessions to allow students to develop schemata for the instructional method.	Scaffolding[38]
		Avoid altering the "rules" of simulation between sessions.	
	Manage emotion	Establish a safe learning environment during the briefing.	Adult learning theory[39]
		Specifically address the social acceptance/necessity of mistakes within the simulation experience, as an essential step toward improved patient outcomes.	
		Establish confidentiality for participants.	
		Explicitly state the nature of any assessment (formative vs. summative).	
Scenario	Avoid split attention	Provide essential patient history from 1 source for novice learners whenever feasible. For example, consider integrating the paramedic report, paper charts, and patient interview into 1 source (eg, a comprehensive patient history)	Modern theories of workload and performance from human factors and cognitive engineering[40]
	Avoid redundancy	If information from the nurse at handover is also recorded on the patient chart that must be read by the learner, then the verbal handover is redundant and learning can improve if one of the redundant sources is eliminated.	
		Interruptions from a administrator-actor to ask for updates and admission plans would be considered redundant (added cognitive load) unless dealing with such interruptions is the objective of the scenario.	
	Use dual modality	When using SPs, make use of the visual processor as much as possible. For example, present vital signs on a bedside patient monitor and provide moulage (or a photo) to portray a skin rash.	Paviio's dual-coding theory[41] Cognitive theory of multimedia learning[42]
	Avoid transient information[43]	When auditory information is complex or lengthy, provide a source of permanent information to limit the high cognitive load of maintaining the information in working memory. For example, encourage note taking or the use of cognitive aids.	
	Provide partially completed or full worked examples	Novice students can be told the interpretation of a test such as a computed tomography scan for pulmonary embolism, rather than interpreting the scan themselves. They can focus their mental resources on management of the patient; computed tomography scan interpretation can be taught in isolation at another time.	Scaffolding theory[38] Vygotsky's zone of proximal development[44]
	Manage emotion and stress	In a scenario in which a family member (actor) is scripted to provide essential information, such as resuscitation status, explicitly instruct actors regarding the degree of worry and/or grief that is required by their character.	Resource allocation model of emotions[45] Processing efficiency theory[46]
	Collective working memory effect	Whenever possible consider interprofessional simulations not only to train for improved team performance but also to enhance individual learning.	Social constructivism[44]
		Train students in dyads rather than independently for technical skills[47]	Bandura's social cognitivist theory[48]
Debriefing	Manage emotion	Always engage learners in a period of defusing (positive and negative) emotions before proceeding to teaching points.	3D model of debriefing[49]

and several applications to medical education have recently been reviewed.[35] We will discuss some of the effects in the context of healthcare simulation training in the following sections. Table 2 provides several specific examples of how these design principles might be applied to teaching with simulation. Because CLT has evolved from key aspects of human cognition, there is significant overlap between the principles that we will discuss and other theories or conceptual frameworks. We highlight these similarities in Table 2 with associated references. However, CLT is unique from many of the referenced frameworks in that its effects were generated from the results of randomized and controlled trials in which cognitive load, hypothesized to be on the causal pathway between the intervention and the outcome, was measured. We believe that CLT will prove to be a useful tool to the simulation community for organizing, explaining, and justifying some of the multitude of theoretical perspectives that have already been applied to the practice of SBE.

Medical simulations are highly complex learning environments. Before participating in a simulation, the healthcare learner has spent considerable time studying the background information required for performance of clinical duties. Once starting the simulation, that domain-specific knowledge and skill are required, as well as knowledge and skills about the simulated clinical environment. Consequently, intrinsic load can be high; as well, potentially high levels of emotion and anxiety will also impact cognitive load. As previously discussed, if cognitive load is too high, then learning is likely to be reduced significantly. Cognitive load theory has identified many strategies to reduce intrinsic and extraneous load, which are briefly discussed next with reference to their applications to healthcare simulations.

Managing Intrinsic Cognitive Load

When to-be-learned materials are relatively simple with few interacting elements, intrinsic cognitive load is low and cognitive load issues are not likely to arise. However, interacting elements cause high cognitive load because they must be considered simultaneously in working memory.[50] Nonetheless, complex problems can be addressed by bringing previously processed, organized, and stored information from long-term memory into working memory in the form of schemata or chunks. These elements do not take up precious working memory resources because they have already been learned and can be automatically applied. Through understanding this cognitive architecture, specific instructional strategies have been demonstrated to be effective for optimizing intrinsic load.

Segmenting Effect

One common approach to dealing with high intrinsic load is through segmenting of information. By reducing tasks into manageable chunks and practicing each chunk until it is effectively stored in long-term memory, a large amount of information can eventually be manipulated in working memory in the form of these chunks.[51] This concept is applied routinely in healthcare training when students are instructed in the basic sciences, clinical skills, and paper-based cases before they move onto immersive simulation experiences. The intrinsic load of the simulation experience comes from knowledge or skills that have not yet been consolidated in long-term memory, the simulated clinical environment in which the learner needs to function and interactions between the two. If data required for the exercise have been previously learned, then reactivating it from an existing schema will not have a significant cognitive load effect; however, reinforcing the concept through a novel application will impose intrinsic load and learning will occur as long as cognitive overload is avoided.

In a recent simulation application, Brydges et al[52] demonstrated the effectiveness of segmenting for teaching clinical intravenous catheterization. He found that a group of students assigned to "progressive learning" in which simulator fidelity and task difficulty were gradually increased and learned more efficiently than those students who trained with either a low-fidelity or high-fidelity simulator alone. The low-fidelity simulator presumably avoided cognitive overload in these novice learners compared with the high-fidelity group who learned poorly (although load was not measured). Once the task was "learned" in the low-fidelity situation and therefore stored in long-term memory, then working memory resources were available for incorporation of novel elements imposed by the next level of realism. Why then is progressive learning actually better than low fidelity alone? The answer is most likely because of sequencing effects. By gradually building knowledge in a low-high complexity sequence, learners were able to increase their knowledge stored in long-term memory and ultimately were able to tackle the highest complexity situations and gain the necessary exposure to the highest complexity. Other important mechanisms for learning that are unrelated to cognitive load, including motivation, reflection, and encoding specificity, may also have contributed to improved outcomes. This experiment demonstrates that the complex cognitive processes involved in consolidating, retrieving, and transferring knowledge might not be possible if the initial working memory processing is hindered by cognitive overload.

Pretraining Effect

In considering a simulation environment, there are multiple elements that are likely to be novel to the learner and on their own and could potentially require large amounts of working memory for task completion. For a medical student who has never been in any clinical environment, the interaction with another healthcare professional and with a bedside patient monitor (with several interacting elements of information displayed) could be overwhelming. Even for experienced clinicians, there could be a several new items of information related to the simulation experience: Where are the pulses and heart sounds on this particular mannequin? Do the pupils react? Do I ask the nurse or the patient for a list of medications? Although the best way to introduce the learners to the simulation environment has not been studied, there are some data from cognitive load experiments that can guide our practice.

Mayer et al[53] used narrated animations to teach college students how brakes work. Learners had to understand what individual components did (how the brake piston moves), as well as an overall causal model (relations between the piston movement and the brake fluid), placing heavy demands on working memory. Best results were obtained by pretraining on components (names and behaviors) initially before learning about the causal effects. Mayer et al[54] also applied a cognitive apprenticeship model[37] for teaching geology to college students, and they demonstrated that those who received pretraining on illustrations of key geologic features (eg, a ridge) showed superior problem-solving performance. In a study of mathematics instruction using spreadsheet analysis,[38] high school students learned more when they were instructed in the use of Excel spreadsheets before instruction in mathematics rather than learning both concepts concurrently. Training on some elements initially allowed for schema construction to occur before teaching interactions.

Similarly, the information related to the simulation environment (and not the case content) is a potential source of high intrinsic load for healthcare learners. Adhering to a practice of routine and detailed briefing of the simulation environment as part of each session will enable the creation of "simulation schemata," thereby freeing working memory resources for optimal learning during the scenario. It follows that the time spent briefing a simulation should not be trimmed when time is, all too frequently, constrained.

Maintaining the same "ground rules" between sessions for returning learners is strongly recommended. If students need to reconsider instructional details each day, such as whether they are expected to deliver medications in real-time versus pretend to push drugs, then that new information will need to be processed in working memory on each occasion, engendering higher intrinsic load.

Connections to Scaffolding

These strategies and others described by CLT theory[1] advocate a simple-to-complex sequence, and sequencing has long been considered an important teaching strategy both for individual learning episodes (CLT) and in full training programs.[36] Effective sequencing has close associations with the concept of *scaffolding*. Generally, scaffolding has a broad meaning and can refer to any type of guidance given to a learner. For example, Clark et al[55] refer to scaffolding as an instructional strategy that provides enough support to reach the intended learning outcomes and can take a variety of forms such as visual aids and on-screen pedagogic agents. Such aids are specifically designed to help learners deal with high intrinsic cognitive load due to task complexity. There are also parallels with the work of Vygotsky[44] who believed that there is a zone of proximal development, which represents a gap between the existing developmental level of a learner and a potential level. Learners cannot reach this desired level alone without help from teachers or peers. Consequently, they need to be scaffolded through this zone with well-designed instruction. Whereas most of the CLT strategies can be considered scaffolds, the ones that reduce intrinsic load are specifically aimed at reducing problem complexity.

Managing Extraneous Cognitive Load

Most work within a CLT framework has investigated the negative consequences of extraneous cognitive load caused by inappropriate instructional procedures. As indicated later, many of the established effects are relevant to teaching with medical simulators and we describe additional practical applications in Table 2. The recently described cognitive load consequences of emotional activation[4] are of particular relevance to simulation instructors.

Worked Example Effect

When presented with a problem or goal, novice learners will typically engage in problem-solving strategies, such as means-end analysis,[56] that require a high degree of mental effort. The result can be that inadequate cognitive resources remain for actual learning. Several lines of evidence clearly support the superiority of an instructional method in which the procedure for solving the problem is provided for study.[19,57–60] For novices, studying worked examples is usually more effective than solving the equivalent problem and this has been designated as the *worked example effect*. Worked examples are another form of scaffolding, because learners would not be able to learn the materials through their own problem solving and need the assistance of expert help presented through the worked example. While learners acquire more practice and develop schemata that allow them to recognize and categorize a problem, then guidance is typically faded.[61] Fading typically involves leaving out steps in the given solutions. While expertise develops, more steps are left out for the learners to complete until the students are able to solve the problems unaided.

One way in which a worked example can be provided in the simulation laboratory is with the "call for help," often incorporated as an opportunity for students to practice effective resource management. When the instructor enters the scenario and demonstrates the appropriate problem-solving strategy (scaffolding), then the high cognitive load imposed on learners trying to solve the problem is reduced and working memory resources can be reallocated to learning. The literature on worked examples also suggests that pairing a worked example with a subsequent similar problem to be solved in its entirety is an excellent strategy for learning.[62] This type of approach has been advocated by Zigmont et al[49] who recommend that simulation learners be given a second opportunity to experience the same case after debriefing. This approach is also consistent with the active experimentation phase of Kolb's learning cycle, frequently referenced in simulation education.[2] Thus, simulation instructors can be reassured that these common instructional techniques have a sound theoretical basis—students will often learn better when they are provided with the full answer to a problem or a partial answer depending on the levels of expertise.

Split-Attention Effect

The split-attention effect occurs when learners must divide their attention between 2 or more sources of information that are separated either spatially or temporally. If the 2 sources of information presented are essential to understanding the content of the exercise, then working memory resources are required to mentally integrate the disparate elements. This mental load is extraneous to learning the targeted task, and studies have repeatedly shown improved learning when sources are presented in an integrated format.[8] Cierniak et al[24] provided a relevant example of this effect when he asked university students to learn about the structure and physiology of human kidneys. Very dense explanatory text positioned alongside a diagram (split-attention format) led to poorer learning outcomes than using the same text fully integrated inside the diagram.[26]

In clinical medicine, the reality is that attention is often divided. Educators need to think very carefully about the overall objectives of a given scenario when they design the flow of information. If a very realistic scenario is fraught with split sources of information, then integrating those sources might impair realism, but it will reduce the extraneous load caused by split attention and potentially improve learning. Distractions are common in medical practice, and simulation studies have shown that they cause errors, reduce performance, and irritate practitioners.[63] Managing divided attention is a real concern for practicing clinicians,[40] but we cannot find any evidence that intentionally providing split-source information during simulation training benefits learning outcomes or the ability to manage such distractions in practice. This is an area for future research but for novice learners, CLT research has clearly shown that unnecessary interruptions and distractions should be minimized to optimize learning outcomes.[8]

Modality Effect

Rather than integrating a diagram with written text to overcome the split-attention effect, the modality strategy advocates the concomitant use of spoken text.[64] By providing explanatory text verbally through some recording or directly by the teacher, learners are able to listen and focus on the visual presentation simultaneously. Search processes are reduced and split attention is avoided. It is assumed for this effect to occur that both sources of information are relevant for learning in combination. The dual modality strategy engages both the auditory and visual channels of working memory described by Baddeley[6] and also taps into the dual-coding theory of Paivio[41] who argues that stronger representations of the concepts are formed by using both channels. One excellent example of the modality effect is from a study in the domain of electric engineering in which investigators found that learning was superior using a spoken text and diagrams compared with identical written text with the same diagrams.[65] A second group replicated this effect in an interactive agent-based environment for learning electronics.[66]

Evidence for this cognitive load effect has been summarized in a meta-analysis of 43 published studies.[9] The modality effect certainly supports immersive simulation as an instructional technique given its multimodality nature; however, it reminds those instructing with SPs or task trainers to also engage both sensory channels when feasible. For example, SP cases are often scripted as primarily auditory experiences, focusing on communication skills. If the SP has a history of rash or joint swelling, then providing a picture or moulage instead of a verbal description can reduce the load on the auditory channel. When creating instructional videos for technical skills, narration will be more effective than concomitant text instruction.[42]

Redundancy Effect

The need for learners to integrate and cross-reference redundant instructional materials can also impose an extraneous cognitive load. Cognitive load theory defines redundant materials as those that are independently intelligible but not essential to the learning activity. This might be duplicate information in a different format (eg, providing both text words and speech during a PowerPoint presentation) or distracting nonessential information (eg, PowerPoint sounds and visual effects). The type of information that contributes to redundancy is that which can be understood on its own and, in this way, differs from the split attention materials in which the 2 (or more) sources of complementary information must be integrated to comprehend the materials. Mayer et al[67] described the redundancy effect specifically for multimedia learning as the situation in which the use of text and speech was worse than presenting words solely as speech. Chandler and Sweller[11] further demonstrated the redundancy effect in other instructional formats including written materials for learning biology and for electric circuitry. In healthcare simulations with multiple learners, providing laboratory results on paper (or a small computer) could potentially create redundancy because the written information often needs to be shared aloud for all to hear. Providing results on a large screen available for everyone to view at their own pace might be preferable because some learners will not have to attend to the same information twice.

Expertise Reversal Effect

Simulation instructors frequently need to adapt their scenarios and teaching techniques for varying learner groups or levels of learners. This challenge can be framed and potentially eased by an understanding of the well-established expertise reversal effect, a CLT effect caused by differing knowledge levels.[10] According to the expertise reversal effect, an instructional design that is beneficial to a novice learner may be detrimental, rather than just neutral, to a more experienced learner and vice versa. For example, in the case of split attention discussed previously, more experienced learners who have gained experience and knowledge might actually find an integrated source of information to be less helpful and, at some point, deleterious to learning. The best instructional format changes with expertise, and this change is explained by the organization of acquired knowledge into highly complex and variably automated schemata in long-term memory.[67,68]

Consider the following example of the potential effects of split attention, expertise reversal, and redundancy during simulation training. Medical educators understand that healthcare practitioners must obtain patient histories from a variety of sources. Accordingly, in simulation, the nurse "actor" often provides the case introduction with demographics and chief complaint and then learners are expected to extract further information from the patient, family members, and/or the chart. This requires the learner to maintain some information in working memory, while searching for novel elements and processing the interactions between these sources of information. This results in a large working memory load due to the split attention effect. For novice learners, it might be cognitively more efficient to provide the learners with a single source of information, such a comprehensive patient history. Cognitive load theory tells us that for novices, this integrated information will engender a lower cognitive load and result in superior learning compared with the conventional split-source format.[8]

However, more senior learners such as residents or nurse practitioners could find such an integrated format to be onerous. As evolving experts, they are already adept at processing information from multiple sources because of preformed schemata regarding where to search and find specific data. For example, a list of medications from a reliable database can be quickly scanned for pertinence to the overall clinical presentation and would likely be preferable to having to verbally extract the medication name, route, and dosing schedule from the patient. The advanced learner already has some knowledge; for example, the typical dose of a baby aspirin for primary prevention, and the redundancy effect states that collecting such redundant information can impose an additional cognitive load.[69] For the more experienced learners, it is preferable to use conventional data-gathering procedures rather than an integrated procedure that was designed to reduce split-attention effects in novices. Thus, the best instructional procedure reverses depending on the expertise of the learners, consistent with the expertise reversal effect. Simulation instructors need to recognize that how the information is presented will affect the mental resources available for learning. In addition, the effect of the presentation method on learner's cognitive load will depend on learner previous experience. Again, these cognitive load implications for scenario design must be considered alongside techniques to motivate learners to effortfully engage in the learning opportunity. Whereas novice learners may be unmotivated by activities beyond their level of development, more experienced learners will be motivated by realistic challenges.

Cognitive Load Due to Emotions

The previous sections outlined the 2 most common forms of cognitive load (intrinsic and extraneous) as investigated by CLT researchers. Very little CLT research has been conducted into the affective domain and how it impacts on working memory and learning. In the past few years, medical simulation researchers have contributed to an understanding of the role of emotions on cognitive load. The full relationship between emotions and learning is complex, but the established effects include the following[70,71]: (1) positive emotions generally increase learning mediated through motivation and attention, (2) positive emotional states improve learning by enhancing cognitive processes such as problem solving and creativity, (3) recall of learned information can be dependent on whether or not the mood of the learner trying to recall information is similar to the mood at the time of encoding, and (4) negative emotions can have differential effects on learning, depending on the situation. The following sections describe how emotions generate both extraneous and intrinsic load.

Emotion as Extraneous Load

Interesting details have traditionally been added to simulations for a variety of excellent pedagogic reasons,[72,73] but some of those additions come with emotional content, and it is becoming increasingly clear that emotions can exert an extraneous cognitive load. Recently, Um et al[74] induced positive emotions during learning in a multimedia environment (by using specific shapes and colors) and they showed that emotion-induced changes in comprehension and knowledge transfer were related to cognitive load.[71]

The simulation laboratory provides a unique opportunity for studying the relationship between affect and learning because participants' emotions are inevitably activated. The broad range of emotions experienced in simulation training can include those related to the patient's health and psychological status, peer pressure, frustration with the environment, and self-monitoring. Fraser et al[4] asked students to rate their emotions after a simulation session on an 8-item Likert type scale anchored by the bipolar descriptors of emotions described by Feldman Barrett and Russell.[76] Results from first year medical students revealed a positive association between activating emotions and cognitive load. Very high levels of cognitive load were associated with poorer learning outcomes.[4]

Obviously, patient outcome can impact learner emotions in simulation, particularly if the simulated patient dies. A recent review[77] of mannequin death described the potential benefits of the practice as a way to teach about death and dying, to increase realism, and to generate buy-in. Cons included the potential for psychological harm to students, particularly novice learners, although cognitive load effects on learning were not discussed. In a recent randomized controlled trial of final year medical students participating in simulation, the unexpected death of the simulated patient increased the report of negative-activating emotions compared with the control intervention, mannequin survival.[75] Learners who experienced the mannequin death were also found to have higher self-rated cognitive load[78] and poorer learning outcomes measured objectively 6 weeks later, compared with the control learners. Among the potential untoward effects of mannequin death during simulations, it now seems that some learners are less likely to reach desired learning goals because of the extraneous cognitive load imposed by associated emotions. Of course, the expertise reversal effect[10] reminds us that the outcome could be completely different when teaching a group of more or less experienced learners.

Emotions as Intrinsic Load

The potential for emotions to overwhelm mental resources must be considered when instructors augment the emotional experience to meet goals of reflection and realism.[79–81] However, within a cognitive load framework, emotional load might not always be extraneous. Extraneous load is defined as load that is not essential to the learning task. If the specific task to be learned is an emotional one, such as a scenario on delivering bad news, then the related content, including the emotional experience, is actually intrinsic to that task and cannot be omitted. In the aforementioned randomized controlled trial on patient death during a simulation, the clear objectives of the exercise were related to the diagnosis and management of a patient with an altered level of consciousness. In that case, simulated patient death adversely affected learning of the objectives because the evoked emotions were not required to achieve the instructional goals. The emotional manipulations in simulation scenarios are often more subtle than mannequin death, such as an upset family member or an unhelpful colleague. Nonetheless, the decision to add such details should be made by weighing up the importance of the emotional context for achieving learning objectives versus the risk that learning will not be successful if working memory limitations are surpassed.

Acute stress is a common learner experience that can contribute to emotional extraneous load. In psychological terms, stress refers to the biological and emotional responses when encountering a threat that one feels that he/she might not have the resources with which to cope.[82] Stress is a highly individualistic experience that depends on specific psychological determinants that trigger the physiological response. The complex relationships between stress, learning, and performance have been studied primarily by measuring cortisol levels and the response of the sympathetic nervous system. One established mechanism for impaired learning and performance under stress is a "reduction" in the size of working memory because valuable working memory capacity is allocated to the anxiety and cognitive processes associated with the perceived threat,[83] consistent with an extraneous cognitive load effect. However, this reduction in working memory has not been previously framed as a cognitive load effect, nor has CLT generally concerned itself with effects of emotions on learning. Fortunately, CLT researchers are increasingly interested in applying their theory to more authentic, complex learning environments[84] just as medical educators are appreciating the importance of applying the cognitive sciences to research in SBE.[85]

Importantly, stress is also known to exert effects on many of the other processes involved in memory and learning as depicted in Figure 2. Specifically, memory consolidation (ie, long-term memory) seems to be enhanced by stress (and the accompanying cortisol response) that is directly related to the task to be learned[86,87]; however, memory retrieval is generally impaired.[88,89] These differential effects of stress on memory processes are incompletely understood and likely account for the inconsistent reports of stress either enhancing or impairing learning. In a recent comprehensive review of the stress effects in simulation training, LeBlanc[90] recommends that to enhance memory consolidation, one must ensure that "the source of the stress is intrinsically linked to the information that is to be learned. If the source of the stress is peripheral to the task, then learning will not be enhanced." These recommendations are in keeping with a cognitive load perspective of minimizing stress when it imposes an extraneous load. We would add that even when stress is deemed to be relevant to the training goal, the overall capacity of working memory should not be exceeded.

Achievement Emotions

Another source of emotional activation during simulation training is that of "achievement (academic) emotions," defined as those emotions that are directly linked to learning, instruction, and performance.[91] Pekrun's control-value theory[7] suggests that all academic emotions arise from a cognitive appraisal of the controllability of success or failure and the value assigned to the task by the learner. For example, during learning in simulation, a student might experience enjoyment as an achievement emotion because he or she is engaging in an authentic experience that will improve future clinical performance (high value). Alternatively, students could become frustrated if they feel that the simulation mannequin is not a realistic representation of a human patient and they have difficulty, for example, with hearing the breath sounds (low control of success). The perceived attitudes of peers and mentors during the simulation exercise could also affect the value assigned to the task by the trainee, and, accordingly, the academic emotions experienced.

Accordingly, from a cognitive load perspective, the importance of the "safe learning environment" cannot be overstated. Instructors generally establish group trust and respect by setting explicit confidentiality rules, clear expectations, and a commitment to collective learning from errors, rather than blame or humiliation of individuals.[92] Educators expect that students will engage in deeper reflection when they are feeling psychologically comfortable and pleasant student experiences should contribute to the ongoing integrity and success of simulation programs.[93] Furthermore, human factors research suggests that healthcare teams perform better when members report feeling "psychologically safe."[94] We now propose that this well-established simulation principle of ensuring learner safety probably also improves learning outcomes by optimizing academic emotions and reducing the associated extraneous cognitive load. We need to better understand how to build trust within healthcare teams during simulation training and in practice,[95–97] and we believe that measuring emotions and cognitive load will provide insight into the effect of psychological safety on learning and performance.

In summary, emotions and stress are well known to affect learning outcomes and they do so, in part, through effects on working memory. The additional demands placed

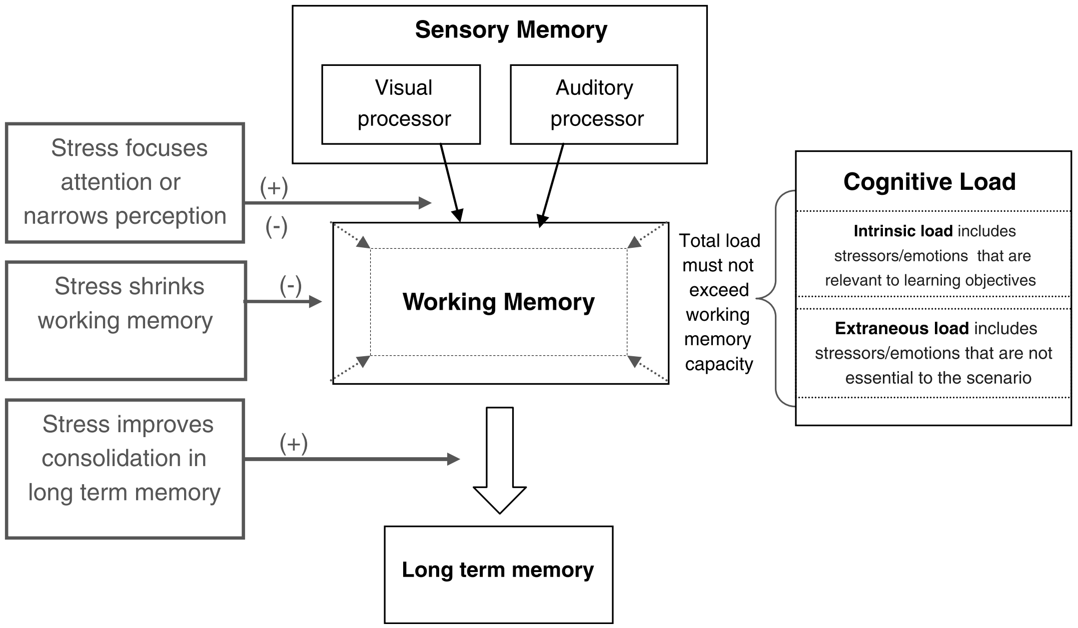

FIGURE 2. Stress, cognitive load, and memory. (+) indicates a potential benefit to learning; (−), a potential impairment to learning.

on working memory to attend to the emotions of the learner could potentially overload mental resources. Because emotions are intentionally manipulated in simulation sessions, it behooves us to consider the balance of detrimental with beneficial effects.

LIMITATIONS AND FUTURE DIRECTIONS

Although CLT has been able to generate new findings and explain old findings, it does have clear limits. The primary concern in applying this theory to healthcare simulations is that the framework has been largely derived from experiments in traditional classrooms with relatively novice learners. Nonetheless, several research articles on teaching with simulation in the past 2 years cite CLT as an important conceptual framework for their findings. Because this trend continues, we will learn more about how the limits of human cognition affect simulation trainees; but to do so, we must first understand the underlying basis for this theory including the details of its established effects.

The major difficulty in applying CLT principles to simulation is in the complexity of simulation environments as compared with the relatively simple teaching platforms in which CLT has traditionally been tested. Defining "extraneous load" as that due to poor instructional design makes sense when the problem to be solved is completely under the control of the instructor, for example, in a mathematics classroom. However in simulation settings, there are multiple "uncontrollable" variables that can be significant sources of extraneous load, including mannequin malfunction, over-zealous actors, or students doing something that was not anticipated by the simulation designer. However, an instructor with an understanding of CLT principles can try to identify and mitigate such potential sources of extraneous load in a proactive fashion. For example, dry runs of scenarios can identify and remediate technical difficulties, actors can be carefully scripted, and "what-if" contingency plans can be provided to all individuals involved in the scenario delivery.

One of the most controversial aspects of CLT has been the term "germane load," which was added to the CLT framework in the mid 1990s to explain how some additional cognitive loads could be beneficial to learning, when earlier work in the field had always advocated reductions in cognitive load. It was introduced when empirical findings demonstrated that not all cognitive load is bad; indeed, learning will not occur without effortful cognitive processing and its associated mental workload.[98] Classic examples of "germane load" include variability in practice and self-explanation, through which learners are encouraged to process data more deeply, creating more flexible and elaborate schemata. In that way, the additional load of the task might be beneficial to learning and especially to transfer, so long as working memory limitations are not surpassed. Since then, germane load has been reconceptualized as a component of intrinsic load. For example, Paas and Van Merriënboer[22] improved learning outcomes in college students studying geometry by adding variability to the training materials. The additional "germane" mental workload was intrinsic to the task because the task itself was expanded to include recognition and classification of the problem types. Brydges et al[99] applied this principle to orthopedic task training for medical students and residents by assigning them to practice tasks in random versus blocked order. In that case, the expected benefit of contextual interference was not realized and the authors hypothesized that the high complexity of the task with the added variability challenge might have overloaded learner cognitive resources. When germane load is conceptualized as intrinsic material that encourages deeper processing of content, then realism and/or emotion can potentially improve learning through a germane-load effect, particularly in the more advanced learner for whom the intrinsic nature of the original task might not be high.

Until recently, CLT has been largely silent on affective and personality issues such as emotions and motivation. To the simulation instructor, these issues are integral to training and cannot be ignored. New conceptions associated with emotion during simulation have been introduced here, and there are many unanswered questions including how best to measure emotions and whether emotions themselves affect measurements of load. Clearly, motivation is essential to learner engagement, and without it, cognitive load issues are actually irrelevant. However, manipulations in simulation that aim to motivate learners, largely based on adult learning theory, can carry cognitive load consequences particularly for novices. At present, we would recommend that extraneous details introduced for purposes of motivation be carefully considered for their potential to overload learners based on learner experience and previous knowledge. The effect of simulation on motivation and, in turn, on learning is an area that is in need of much study.

One new promising direction for CLT concerns collaboration, because most of the research to date has been conducted with individuals. Collaborative learning environments have a long history of being highly advocated, usually based on a motivational perspective—students are motivated by being grouped together, or from a social constructivist point of view, knowledge is best constructed by discourse between students.[44] In healthcare circles, interprofessional training is emerging as an essential component of educational programs aiming to prepare trainees for a collaborative work environment. In recent studies, Kirschner et al[100,101] conceptualize collaborative learning from a CLT perspective. A key aspect of their hypothesis is that for complex problem-solving situations, group members can effectively reduce their collective working memory load by working together. Instead of learners trying to solve problems that might overload individual working memories, by sharing the load through collaboration, individual loads are reduced and learning improves. Recently, CLT researchers showed that worked examples are an effective strategy for middle school children in collaborative settings.[102] Similarly, medical students training in pairs (as compared with alone) on a medical simulator reported subjectively that they "benefitted from a united memory of the prior instruction."[47] Salas et al[103] has clearly demonstrated that the "sharing of mental models" improves team performance through better communication, understanding of common goals, and anticipation of the actions of others. Could an additional advantage of training healthcare learners in groups be improved learning outcomes?[104]

To sum up, CLT has dramatically improved instruction in many educational domains and it is time for the simulation community to examine its practices under this lens. The simulated learning environment is complex with a potentially high cognitive load that must be recognized and carefully managed in relation to learner previous experience. Recent data have shown that a failure to learn in the simulation setting can be related to cognitive load, but much research is required into how this finding should inform the design of simulations. The incorporation of cognitive load measures into ongoing research in simulation could help quantify the relevance of this theory for our field and provide an additional framework upon which to interpret emerging results.

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