Issue Brief 17

Cognitive Load Theory and Its Impact on Diagnostic Accuracy

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Introduction to Diagnostic Errors

Diagnostic errors, or "the failure to establish an accurate and timely explanation of the patient's health problem(s) or communicate that explanation to the patient,[1]" are a leading cause of patient harm. *To Err Is Human*,[2] a report published by the Institute of Medicine in 1999, was one of the first publications to bring the issue of medical error, patient harm, and the need for safer systems to a national stage.

Improving Diagnosis in Health Care,[1] published in 2015, continued the patient safety discussion with a focus on the impact of diagnostic errors on medical harm. This report suggested that diagnostic errors may contribute to 10 percent of all patient deaths. In addition, diagnostic error may result in serious harm to more than 500,000 Americans each year across ambulatory, emergency, and inpatient care settings.[3]

In a more recent study of almost 2,500 medicine patients who died or were transferred to the intensive care unit, diagnostic errors were found in 23 percent of cases.[4] While the cause of these delayed, missed, or wrong diagnoses are almost always multifactorial, most cases have some contribution from inaccurate clinician diagnostic reasoning.[5,6] Diagnostic reasoning is the process by which a clinician uses medical knowledge, critical thinking, and experience to gather, integrate, and interpret clinical information. Then, the clinician generates a working diagnosis, creates a testing plan, formulates an accurate diagnosis, and communicates this diagnosis to a patient.[1,7]

Unfortunately, identification of inaccurate diagnostic reasoning and diagnostic error often takes place after the error has occurred. Retrospective investigation into the contributing factors that led to the diagnostic error are subsequently at risk of biases. These include hindsight bias and outcome bias. Hindsight bias is overestimation of one's ability to predict a correct diagnosis had one been asked to do so before knowing the diagnosis. Outcome bias is difficulty accurately judging a decision after the outcome of the decision is known, rather than based on the information available at the time of the decision.[8]

Diagnostic reasoning has historically been treated as intrinsic to the individual clinician, likely due to difficulty visualizing and measuring cognition based on the inherent complexity and internal nature of mental processes. However, there is now growing recognition that cognition is complex and affected by context, cognitive biases, resources, and physical, social, and technological environments.[9] Increasing attention is also being given to cognitive load theory (CLT), an educational model for how human memory and processing occur, with a focus on how to optimize the limited resources of cognitive capacity.[10]

Studies have already found that cognitive overload reduces decision-making flexibility,[11] is associated with task errors,[12] and can promote default thinking rather than conscious and analytical thinking.[13] However, CLT as it applies to diagnostic accuracy is a relatively new area of study, with most of the research occurring in the last 5 to 10 years.

This AHRQ brief will provide a broad overview of fundamental CLT concepts, discuss what is and is not yet known about the interplay between CLT and diagnostic accuracy, and review ways to measure CLT to understand its causal impact on diagnostic accuracy. The brief will conclude with recommendations for future research and improvement efforts, with the goal of better understanding how cognitive load affects diagnostic accuracy and how to optimize cognition to decrease diagnostic error-related morbidity and mortality. A clinical vignette will be woven throughout the paper to better illustrate the concepts and provide clinical context.

Fundamental Concepts for Understanding Cognitive Load

A basic understanding of CLT is required to understand how cognitive load impacts clinicians and healthcare systems. CLT was first developed in the 1980s and focused on human information processing, memory, and problem solving within education.[14] Importantly, CLT did not attempt to directly measure cognitive load, but rather described a theoretical lens with which to view human learning.[15]

Since then, there has been growing awareness that CLT provides a useful framework beyond the educational sphere and that key concepts can be applied to diagnostic reasoning.[16] Cognitive load has two key domains composed of types of memory and types of cognitive load, which are discussed below.

Types of Memory

The first key CLT domain describes types of memory. Memory is the neurochemical and psychological process linked to information processing, encompassing tasks such as encoding, storage, and subsequent recall.[17] Memory, as it applies to CLT, can be broken into three subcomponents: sensory, working, and long-term memory.

Sensory memory allows sensory input to be filtered and, if relevant, passed on to working memory. Sensory memory has huge capacity, but information exists for mere seconds before being forgotten or passed on (e.g., continuous processing of all visual, auditory, tactile, gustatory, and olfactory input with transient conscious awareness of only relevant stimuli, such as an alarm).[10]

Working memory contains actively processed information and executes intentional cognitive tasks. Working memory can hold five to nine pieces of information at the same time and critically analyze around four pieces of this information.[18] Unless effort is taken to transform these pieces of information into long-term memory, working memories will be lost within 1 minute (e.g., being told an unusual medication dose by a pharmacist and placing the order, without being able to later remember the dosing amount).

Finally, long-term memory is the theoretically infinite memory space that can store cognitive schemas and facts for subsequent recall (e.g., intentional memorization of a diagnostic approach to anemia).[10]

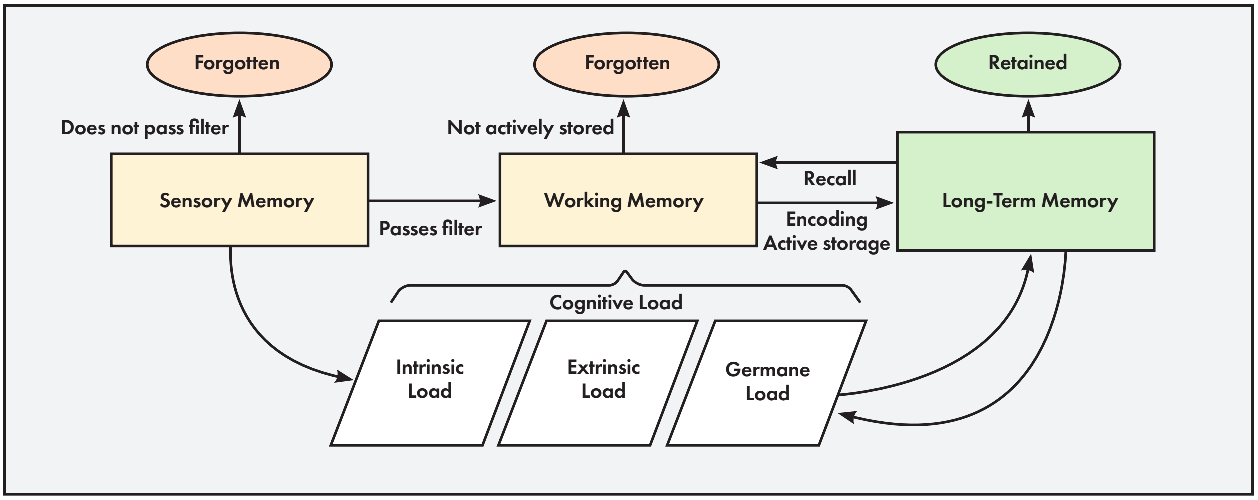
Types of Cognitive Load

The second key CLT domain describes types of cognitive load. Cognitive load is the amount of information stored in working memory at any one time and can be broken into three subcomponents: intrinsic, extrinsic, and germane load. Intrinsic load is information critical for the task (e.g., effort required to learn a new task, process relevant clinical information, or perform procedural steps).

Extrinsic load is information present but detrimental to the task. It can include information presented in an ineffectual way (e.g., overly complicated electronic record visuals). It may also include load from the external environment (e.g., chaotic surrounding environment) or load from the internal environment (e.g., stress from a recent negative patient interaction).

Germane load is the load imposed by deliberate use of cognitive strategies for long-term memory formation and learning (e.g., diagnostic schemas and procedural automation).[13,19] Figure 1 shows the interplay between types of memory and cognitive load.

Figure 1. Conceptual map of cognitive load theory key domains



Clinical Example

Consider the following scenario to better understand how CLT might apply to a clinician as they perform diagnostic reasoning.

A hospitalist is admitting a patient with presumed new heart failure from a busy emergency department. As the hospitalist enters the patient's room, various types of memory become relevant. They begin to unconsciously process relevant and irrelevant sensory information; they note the room number and patient's voice and face, while filtering out sirens from outside, telemetry beeps, and chaos from the code occurring across the hall. They also begin to recall from their long-term memory the pathophysiology of congestive heart failure. All relevant information from both sensory and long-term memory is brought into their working memory but, based on working memory constraints, they can only critically analyze and apply around four of these memories at a time.[18]

The hospitalist is also simultaneously handling various types of cognitive load. They manage intrinsic cognitive load demands as they assess for elevated jugular venous pressure, analyze the electrocardiogram, and ask the patient about symptoms of volume overload. They manage extrinsic cognitive load as they concurrently process unrelated "best practice alerts" from the electronic health record (EHR), messages from nurses about other patients, and stress from worrying about a sick family member. Finally, they use germane cognitive load to pull in congestive heart failure diagnostic schemas to compare this patient's clinical presentation with their typical representation of a patient with heart failure.

When you consider all the cognitive processes that must occur with reasonable precision during the diagnostic reasoning process to accurately diagnose this patient with decompensated heart failure, the complexity of cognition needed for this relatively simple clinical task becomes clear.

Interplay Between Cognitive Load and Diagnostic Accuracy

During diagnostic reasoning, most clinicians apply a variety of cognitive techniques to arrive at a diagnosis. However, surprisingly little research has been done when it comes to causally establishing that high levels of cognitive load may lead to worse diagnostic accuracy. Although not explicitly stated in the literature, this situation is likely due to the difficulty of objectively measuring cognitive load because it inherently occurs in the internal cognitive environment.

As discussed below in the "Measures of Cognitive Load" section, cognitive load cannot be directly visualized and cannot be easily measured with objective tools. Rather, most measurements rely on subjective retrospective tools such as self-reported questionnaires or use objective proxies such as heart rate variability to infer amount of cognitive load. However, two areas that do have some evidence for causality between increasing cognitive load and decreasing diagnostic accuracy are cognitive overload and dual-process thinking.

Cognitive Overload

Cognitive overload occurs when working memory becomes overly burdened, leading to a decreased ability to learn, accurately process information, and execute performance-based tasks effectively.[11] Although cognitive overload can occur in many settings, it is most often caused by information overload, multitasking and interruptions, and environmental threats.[20]

Information overload can occur when a clinician is forced to process excessive or unnecessary information. Within healthcare, this overload can take many forms but can most easily be divided into pushed (passively given to the clinician) and pulled (actively sought by the clinician) information.[20]

Pushed information is information over which the clinician has little control, such as electronic data, including vast amounts of sometimes poorly organized or redundant EHR data, electronic messages, and information from the patient and other healthcare workers. Pulled data includes information being actively sought, such as the same information streams that produce pushed data, but also include other avenues of research, such as books and online databases.

Pushed and pulled data can contribute to both intrinsic and extrinsic load. When the data are overwhelming, poorly organized, or irrelevant to the primary task, extrinsic load will disproportionately increase, resulting in less intrinsic load capacity to dedicate to the task at hand. In one study, a novel EHR interface designed to minimize extraneous data in a critical care setting reduced subjective workload scores, time for task completion, and number of cognitive errors associated with the assessment of a theoretical bleeding patient.[21]

Multitasking and task switching can also lead to cognitive overload and result in diagnostic errors.[22] When a clinician is interrupted or asked to perform two simultaneous tasks extraneous to their primary task, they have to process information unrelated to the primary task, which increases overall cognitive load (in this case, via an increase in extrinsic load).

In some cases, the clinician has to set aside information being used for their primary task to increase working memory reserves for the secondary task. Switching back to the primary task requires both remembering to return to the task after the interruption and efficient retrieval of all information previously being used for the initial task. In one study of 18 emergency department healthcare workers, only 87 percent of interrupted clinical tasks were resumed after the interruption.[23] In another simulated study with 10 intensive care unit nurses, interrupted tasks were temporarily or permanently forgotten 5.5 percent of the time.[24]

If information is not retrieved with a high degree of accuracy, it can also lead to errors.[25,26] In one study, radiology residents had a 12 percent increased likelihood of a diagnostic error when receiving just one phone call above the average baseline number of calls.[27] Further complicating this concept is that some interruptions are more worthy of a clinician's time than others, such as interruptions related directly to the patient at hand or a critical update related to a different patient. However, clinicians have limited ways to decide whether a particular update, alert, or new piece of data is worth interruption at any given time; all distractions happen equally.

While multitasking will always be part of a clinician's job, the ability to triage interruptions is critical. If clinicians cannot selectively engage with interruptions, cognitive overload will occur if too much irrelevant information is presented.[26]

Finally, the environment itself can contribute to cognitive overload. Clinical environments can be auditorily and visually stimulating. Alarm fatigue is widely acknowledged to be a significant patient safety concern,[28] and frequent alarms result in a large amount of extrinsic cognitive load.[29] Chaotic and loud environments in emergency rooms can lead to ineffective patient handoffs and may negatively impact patient safety and diagnostic accuracy.[30] Poorly integrated and visually complex clinical decision support systems, rather than assisting in diagnostic accuracy, can instead lead to cognitive overload and inaccurate decision making.[31]

Hospital environments are uniquely suited to benefit from information ergonomics,[32] especially as it applies to optimizing the cognitive environment, but so far this area of study has been underemphasized.

Cognitive Load and Dual-Process Thinking

Cognitive load also directly impacts dual-process thinking. The dual processing model of cognition posits two main types of thinking processes. Type 1 cognition is fast, intuitive, and easy, while type 2 cognition is slow, analytical, and effortful. Type 1 processing relies on intuition and patterns to formulate a rapid diagnosis. In a fast-paced healthcare environment, this type of processing is needed for efficient and effective healthcare delivery.[33]

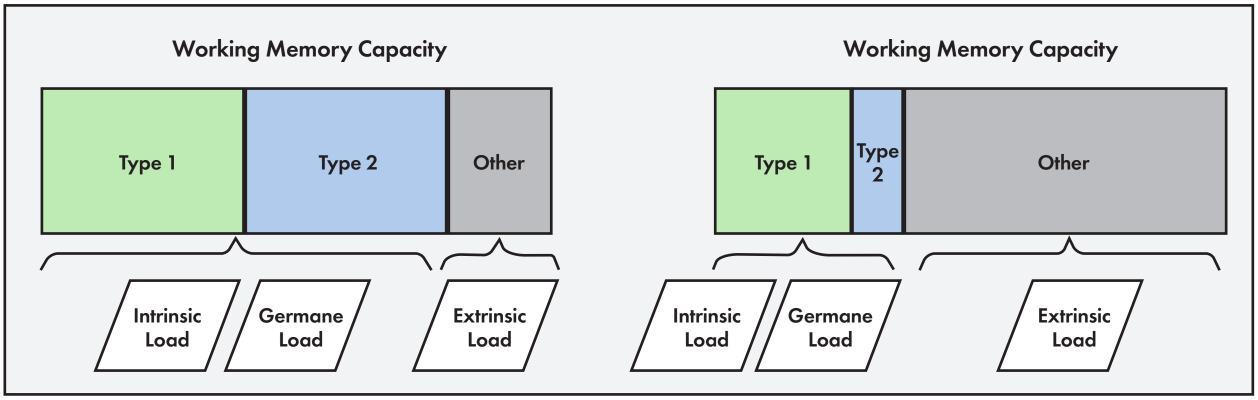
Type 2 processing is required when a clinician has less clinical experience, such as during medical school or in the earlier years of training; when a complex, unusual, or ambiguous clinical problem arises; or when a common clinical condition does not evolve as expected.[34]

One type of processing is not necessarily better than the other. It may make intuitive sense that more rapid and frequently heuristic cognition is more error prone. But type 1 thinking is not universally associated with worse diagnostic accuracy,[35-38] especially among more expert attending clinicians who have spent years building their mental schemas and knowledge base. In addition, type 1 and type 2 processing are often both needed during a clinical encounter.

Cognitive load directly affects clinicians' ability to engage in dual-process thinking. The ability to come to the correct diagnosis, especially in the face of diagnostic uncertainty or an evolving clinical course, is predicated on the ability to quickly and appropriately switch between type 1 and type 2 cognition. However, if working memory is overloaded by extrinsic distractions, the clinician will face cognitive overload and may be unable to switch between type 1 and 2 cognitive processes.[13,39]

Figure 2 illustrates how cognitive load affects cognitive processing. Working memory has a finite capacity. If extrinsic load is low, both type 1 and type 2 thinking can occur. Conversely, if extrinsic load increases, as can occur with a chaotic environment, distractions, unsafe workload, and multitasking, the ability to engage in more effortful type 2 thinking decreases due to the cognitive bandwidth required for this type of thinking. Instead, the clinician will rely on more intuitive type 1 thinking, which can increase the risk of errors in situations that necessitate parallel type 1 and 2 processing or a transition to type 2-predominant processing.

Figure 2. The impact of cognitive load on type 1 and 2 thinking



Clinical Example

The impact of cognitive load on diagnostic reasoning can be explored by returning to the example of a hospitalist admitting a patient with congestive heart failure. As the patient arrives in the emergency department, the hospitalist attempts to look up whether they might benefit from newer guideline-directed medical therapy. But the hospitalist must sift through primary research, meta-analyses, and clinical decision support tools, none of which are integrated within the EHR (information overload).

Next, the hospitalist tries to bring up the patient's record but finds that the patient has duplicate charts and the hospitalist has to toggle between the charts to review baseline lab values and prior diagnostic workups (task switching). Concurrently, they receive multiple electronic messages that they read while listening to the patient describe their symptoms (multitasking). As the hospitalist becomes more cognitively overloaded, they rely more heavily on type 1 thinking to rapidly process the elevated troponin, chest x ray with diffuse haziness, and lower extremity edema.

The hospitalist diagnoses the patient with congestive heart failure. However, they fail to consciously process that the patient mentioned a new cough, do not notice the patient's slightly elevated temperature, and discount the mildly elevated white blood cell count as reactive. Because of limited working memory capacity, they do not switch into type 2 thinking and miss that this patient has multifocal pneumonia in addition to heart failure.

In this example, the presence of overwhelming extrinsic load and cognitive overload leads to a diagnostic error. This error results in a missed diagnosis and lack of treatment for pneumonia, which can progress to more serious conditions, including respiratory failure and sepsis.

Measures of Cognitive Load

To best understand cognitive load's impact on diagnostic reasoning, researchers and system improvement experts must be able to measure it. When CLT was first conceptualized, there were few ways of directly measuring cognitive load.[15] Since then, numerous measurement tools have been developed with the goal of more directly measuring the effects of various interventions on cognitive load. Still, accurate measurement remains a persistent challenge due to the inherent difficulty of measuring an entirely internal cognitive environment.[40]

Measures that do exist can generally be broken into subjective, objective, and electronic measurement tools. Below is a summary of each of these tools; applications in healthcare studies will also be discussed, although research using these tools to directly study diagnostic accuracy is lacking. To better design studies that can causally link unsafe levels of cognitive load with diagnostic error, an understanding of the available measurement tools is needed.

Subjective Measurement Tools

Subjective measurement tools are generally represented by retrospective surveys and questionnaires that aim to measure the respondent's perceived workload or mental effort. The NASA-Task Load Index (TLX), Subjective Workload Assessment Technique (SWAT), and Paas Cognitive Load Scale were some of the first subjective measures created in the late 1980s and early 1990s and are still widely used today.

The NASA-TLX[41] is used across multiple fields, including aviation,[42] healthcare,[43] human factors engineering,[44] and industrial ergonomics.[45] Importantly, the NASA-TLX measures self-reported mental demand and assesses physical demand, temporal demand (i.e., time pressure), performance, effort, and frustration to provide a holistic view of overall workload.

The SWAT is a multidimensional tool created to capture the impact of time load, psychological stress load, and mental effort load to create an overall score for perceived mental workload.[46] The Paas Scale is a 9-point Likert-based tool that can be used for self-evaluation of the cognitive effort required for a task.[47]

The NASA-TLX, SWAT, and Paas Cognitive Load Scale can provide indicators of overall self-assessed cognitive load[48] but are fundamentally interruptive to administer and, by nature, retrospective, which limits their applicability in pragmatic clinical environments.

Surprisingly little research has been done using subjective measurement tools to study if perception of rising cognitive load is associated with increased risk of diagnostic errors. As discussed above, cognitive overload is associated with decreased cognitive flexibility and more simplistic reasoning,[39] which may mean that high levels of cognitive load are an important variable associated with diagnostic errors; causal research into this area is still needed.

Subjective measurement tools have been used to research workload and its associated impact on patient safety in other domains, however. For instance, a recent study found that increased nursing workload in the neonatal intensive care unit was associated with missed nursing care. Interestingly, when the missed care variables were modeled independently, only 7 of the 12 missed care outcomes showed that increased nursing-to-infant ratios were associated with missed nursing care. However, higher NASA-TLX scores were associated with an increased risk of missed care in all 12 missed care outcomes.[49] Higher mental workload can also lead to worse surgical laparoscopic performance[50] and increasing educational workload is associated with reduced vigilance during anesthesia induction.[51]

Objective Measurement Tools

More objective measures of cognitive load have also been developed; like their subjective counterparts, they cannot accurately measure cognitive load subcomponents but can provide an indicator of overall cognitive load at the time of the task, rather than retrospectively. They can broadly be divided into nonphysiologic and physiological measurements.

Common nonphysiologic measurement tools that can be used to study cognitive load are:

- Dual-task methodology (asking a participant to perform two tasks concurrently, with the goal of assessing whether performance drops across either task),[52]
- Trail Making Test (accurate timed connection of nonsequential dots),[53]
- Digit span recall (accurate repetition of a sequence of numbers),[54]
- Stroop task (accurate recitation of mismatched ink color and word),[55] and
- Wisconsin Card Sorting Test (accurate card sorting based on stimulus cards and rule-based feedback).[56]

These tools have commonly been used to study cognitive load and working memory, including recall, error rates, sustained vigilance, and processing speed. A significant portion of the literature focuses on the effect of sleep, shift work, distraction, and fatigue on cognitive function. For example, a great deal of literature links multitasking and fatigue with prescribing errors,[12] cognitive overload with poor performance in simulation training environments,[57] and rapid shift rotation with impaired perceptual and motor abilities.[58]

As with subjective cognitive load measures, surprisingly few high-quality studies have been conducted to objectively study increasing cognitive load and the risk of diagnostic errors, despite a large body of literature linking cognitive overload with other types of medical errors.

More physiologically based measurement tools have also been validated as ways of measuring cognitive load. Eye-tracking studies have shown that pupil diameter and the rate and magnitude of microsaccades change in reliable ways depending on task difficulty and cognitive load.[59] One study found that novice physicians showed higher pupillary responses during difficult clinical questions compared with more expert physicians.[60]

Heart rate and heart rate variability have also been correlated with high cognitive load. Increasing rates were found to correspond with increasing measures of intrinsic cognitive load along with worsened performance during clinical reasoning tasks.[61]

Electronic Measurement Tools

EHRs have introduced a significant change in clinician workflow, with up to 50 percent of a clinician's day now spent in front of a computer.[62] Clinicians also report increased interruptions and alert fatigue from poorly designed decision support tools.[63] Theoretically, EHRs can streamline workflows, reduce cognitive load via clinical decision support algorithms, and improve patient safety. But they can also lead to inefficiencies, cognitive overload, and safety events.[64]

Understanding the impact of EHRs on cognitive load and diagnostic accuracy will be critical to advancing patient safety. Several EHR cognitive load measurement tools include EHR audit log data and EHR usability scales.

Audit log data provide an unobtrusive way to measure clinician workload and workflow. These logs contain time-stamped data about how a clinician is interacting with the EHR and can capture what tasks are performed and the time spent on them. Examples include chart reviewing, use of clinical decision support tools, methods of documentation, and choice of orders.[65]

A validated submeasure that uses EHR audit log data is called the "Wrong-Patient Retract-And-Reorder" (Wrong-Patient RAR) tool. It quantifies how many orders are placed for a patient, retracted within 10 minutes, and then reordered by the same clinician for a different patient. Although this type of error would be considered a "near-miss" since it never reaches the patient, research has shown that near-misses can serve as an early indicator of more serious system faults. Similarly, improvement efforts that decrease the RAR rate should also decrease the number of wrong-patient orders that do reach patients.[66]

EHR audit log data can also be coupled with radio-frequency identification, which is a sensor-based technology that enables movement tracking, to create a comprehensive understanding of clinician workflow, including possible insight into cognitive burden. For example, one study found that some emergency physicians read several charts at one time and then visited multiple patient rooms before returning to document the encounters. Audit log data found that these physicians were less efficient and spent more time documenting this type of encounter, possibly due to higher cognitive burden.[65,67,68]

Audit log data allow a detailed analysis of clinician workflow and workload. Future research should focus on correlating workflow and workload with cognitive load, potentially using some of the aforementioned subjective and objective tools, followed by assessment of the impact on diagnostic accuracy.

EHR usability can also be measured via cognitive task analysis. Cognitive task analysis assesses performance both pragmatically and in simulations and explores how people think. This type of measurement allows assessments about how electronic interfaces may increase extrinsic load and contribute to cognitive overload.[69,70]

Cognitive task analyses have also been used to show that as configured, many EHRs do not help clinicians maintain a "big picture" of the patient, including their current state and what treatments may help.[71] Measuring the impact of technology on clinical workflow is a newer area of research. Given the degree to which technology is now interwoven with clinical care, however, it will be important to understand the impact of this technology on cognitive load, diagnostic error, and patient safety.

Proposed Foundational Research

As discussed above, high-quality studies exploring the causal relationships between cognitive load and diagnostic accuracy are lacking. We propose the following two areas as the most immediate to focus on to create a better foundational framework for understanding cognitive load and diagnostic accuracy:

1. More robust investigation into how high cognitive load impacts clinician diagnostic accuracy in simulated settings. While simulated environments do not perfectly reproduce clinical environments, they allow more precise and replicable manipulation of clinically relevant independent variables intended to increase cognitive load. Such variables may include interruptions and sensory stimuli designed to be distracting, including disruptive electronic messages/pages and alarms.

   Participants could be asked to work through standardized clinical vignettes while being exposed to stimuli designed to increase their cognitive load. Researchers should confirm that these stimuli increase cognitive load via subjective and objective measures (e.g., NASA-TLX surveys and heart rate variability). Once researchers establish that these stimuli reliably increase cognitive load, participants could work through a variety of clinical vignettes while the type and number of diagnostic errors are measured.

2. Pragmatic investigation into how real clinical environments impact clinician cognitive load and diagnostic reasoning. While pragmatic studies can be more difficult to standardize and results can be difficult to generalize, these studies would allow better understanding of how cognitive load impacts clinicians in real patient care settings. As with simulated studies, pragmatic studies could incorporate both subjective and objective cognitive load measures. Clinicians could be asked to wear heart rate monitors that capture heart rate variability and to fill out NASA-TLX surveys at the end of each shift.

   Diagnostic errors are often not identified until after patient harm has occurred (e.g., a missed pneumonia diagnosis may not be recognized on the day that it is missed, but rather when the patient develops complications several days later). Thus, chart reviews could occur after a predetermined amount of time has elapsed to assess for the presence of diagnostic errors.

   Assessments could be done by the treating clinician to allow self-identification of errors, along with a chart review by an independent expert reviewer. The NASA-TLX and heart rate variability scores could then be compared with the number and severity of diagnostic errors.

Once the causal relationships between cognitive load and diagnostic accuracy have been better explored and defined, healthcare systems and researchers can begin to investigate more practical ways to help clinicians optimize their cognitive load to enhance their diagnostic accuracy.

A Future Vision for Better Diagnostic Outcomes

Enhancing understanding of clinician cognitive limitations will be useful in helping clinicians engage in more accurate diagnostic reasoning and in avoiding harmful diagnostic errors. CLT offers a useful framework for understanding diagnostic reasoning and inherent cognitive limitations. Although imperfect, methods for measuring cognitive load do exist.

More research into the causal pathways is needed, but we think we can reasonably state that high cognitive load likely does impact diagnostic accuracy. With this premise in mind, we propose the following hypotheses as the most important to further explore (Table 1). If they prove correct, we have suggested ways to better protect clinician cognitive load with the subsequent assumption that diagnostic accuracy should improve.

Table 1. Cognitive load hypotheses and opportunities to develop enhanced diagnostic accuracy

Hypothesis	Opportunities for Implementation
Cognitive load is an independent variable that affects diagnostic accuracy and should be accounted for when designing clinician workforce structures.	• Create more flexible and innovative clinician workforce structures to decrease cognitive overload (e.g., consider novel ways to distribute patients across teams to account for patient complexity, implement flexible limits to the number of patients seen by a physician, and explore how to best incorporate advanced practice providers to decrease overall provider team cognitive load).
EHR audit log data can serve as a proxy for cognitive load and should be used to help create EHR interventions that protect clinician cognitive load.	• Monitor EHR audit log data to determine which clinicians may be at risk of cognitive overload (e.g., via "wrong patient retract-and-reorder" measurements, number of electronic interruptive alerts and messages, electronic patient panel complexity scores, and amount of time spent in individual patient charts) to help provide real-time support to decrease clinician cognitive load.
Human factors engineers and system usability testing can create technology that decreases clinician cognitive load.	• Human factors engineers should work closely with frontline clinicians during the development of new technology to ensure adequate system testing (e.g., analysis of tasks/clicks required for an action, number of distractions, and time required for a task). • Major technology changes (e.g., EHR updates) should undergo system usability and cognitive load testing before implementation.
Cognitively protected physical spaces decrease extrinsic cognitive load to allow more capacity for intrinsic and germane cognitive processing.	• Create physical spaces that minimize extrinsic load to protect clinical decision-making cognitive bandwidth (e.g., workrooms insulated from disruptive alarms). • Implement shared awareness of the need for protected cognitive spaces during high-risk transitions (e.g., spaces in the emergency room for clinicians to receive uninterrupted handoffs from paramedics).
Cognitive load theory should be integrated into organizational change efforts to better protect healthcare worker cognition.	• Clinicians and organizational leaders should be taught basic cognitive load theory principles to help them better understand and optimize cognition. • Major change efforts (e.g., new EHR interfaces, physical space redesign, new clinician staffing models) should be viewed through the lens of cognitive load theory to minimize extrinsic load where possible so that cognitive processing is optimized.

Clinical Example

What might an environment that focuses on optimizing the cognitive environment look like? A clinical example is again helpful. Consider the hospitalist admitting the patient with congestive heart failure and, unbeknownst to them, multifocal pneumonia. Because this hospitalist works for a division that understands the limits of cognition, their leadership strategically incorporates additional measures of workload via the NASA-TLX. This approach allows customizable limits on the number of patients the hospitalist is expected to care for and acknowledges that provider workload is likely impacted by total census and patient complexity.

In addition, at this hospital, cognitive task analysis was coupled with task-evoked pupillary eye tracking and heart rate variability measurements during EHR interface development. This analysis resulted in an information visualization system that minimizes extrinsic cognitive load by avoiding complicated visuals and data overload. The hospital's EHR has also been customized to allow various levels of electronic messaging urgency, which helps the hospitalist designate protected time during high-risk and error-prone periods and hold nonurgent interruptive alerts, thereby reducing multitasking.

Finally, the emergency room has been thoughtfully designed to reduce alarm fatigue and protect patient rooms from loud noises and unnecessary visual stimuli. Because the cognitive environment has been optimized, the hospitalist avoids cognitive overload and can appropriately engage in dual-process thinking; they realize that their patient has both heart failure and multifocal pneumonia. Appropriate antibiotics are started and sepsis, with its associated high morbidity and mortality, is avoided.

Conclusion

Diagnostic accuracy is garnering increasing interest from researchers, frontline clinicians, and healthcare systems focused on creating safer environments for patients. CLT provides a framework that can be used to better understand cognition, along with its limitations. Further investigation into the interplay between cognitive load and diagnostic accuracy will help create strategies to support clinicians as they optimize their diagnostic accuracy.

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