

COGNITIVE LOAD THEORY IN LEAN CONSTRUCTION: A FRAMEWORK FOR HUMAN-CENTERED TASK DESIGN

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ABSTRACT

Construction projects depend not only on technical resources but also on workers' cognitive capacity to process information, coordinate tasks, and make rapid decisions in dynamic environments. Excessive cognitive demand often manifests as errors, delays, and safety incidents, yet current Lean practices rarely diagnose or address these hidden “cognitive wastes.” Cognitive Load Theory (CLT), originating in educational psychology, distinguishes between intrinsic load (from task-inherent complexity), extraneous load (from inefficiencies in task design or environment), and germane load (from productive learning). This paper introduces a framework for manifesting CLT in Lean Construction, positioning cognitive overload as a form of waste that undermines flow and value generation. The framework unfolds in four steps: (1) mapping cognitive load sources through task analysis, site observation, and worker feedback; (2) monitoring cognitive load; (3) intervening to optimize task design by reducing extraneous load, scaffolding intrinsic load, and supporting germane load; and (4) integrating cognitive metrics into Lean controls. The framework is demonstrated through the case of cutting fiberglass cable trays in a modular yard. This study advances a human-centred approach to task design and project control by embedding CLT into Lean practice. It reframes cognitive overload as a form of waste, thereby enhancing safety and productivity.

KEYWORDS

Cognitive Load Theory, task complexity, human-centered task design, safety, continuous improvement.

INTRODUCTION

The construction industry remains one of the most complex and uncertain sectors, characterized by fragmented workflows, dynamic environments, and high error potential. Despite technological advances in project controls, performance issues such as delays, rework, and safety incidents persist. A critical, yet underexplored, factor driving these inefficiencies is human cognitive capacity. Workers must constantly process instructions, navigate hazards, and coordinate tasks under conditions of uncertainty. Productivity in construction has remained stagnant for decades, with studies consistently reporting lower growth compared to other industries (Barbosa et al., 2017). Traditional project controls such as schedules, budgets, and quality inspections tend to capture issues only after they materialize, offering limited support

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in proactively preventing errors. While Lean Construction practices such as the Last Planner System (Agrawal et al., 2024; Görsch et al., 2025) have improved workflow reliability and reduced variability, they primarily address process inefficiencies rather than the cognitive demands placed on workers. Consequently, the human dimension of task performance—how workers perceive, process, and act under complex site conditions—remains insufficiently accounted for in current productivity and project management approaches (Eltahan et al., 2025c, 2025d).

Cognitive Load Theory (CLT) (Sweller, 1988), originating from educational psychology, provides a powerful lens to analyze how the human mind interacts with complex tasks. CLT distinguishes between intrinsic load (inherent), extraneous load (inefficiencies in task presentation and environment), and germane load (resources devoted to meaningful learning). While CLT has been widely applied in instructional design, its manifestation in construction remains under-theorized and under-implemented. Existing construction studies that address mental workload or cognitive demand through physiological signals (e.g., heart rate variability), eye-tracking metrics, or subjective workload instruments (e.g., NASA-TLX) constrain interpretation to observed workload levels rather than explaining the mechanisms driving cognitive demand or informing targeted interventions (Akanmu & Okoukoni, 2018; Elmousalami et al., 2025; Jebelli et al., 2016). As a result, observed workload fluctuations are frequently reported as descriptive outcomes rather than being interpreted through a theory-driven lens that explains why cognitive demand arises and how it can be systematically reduced. Moreover, most construction productivity and Lean research conceptualize inefficiencies primarily in terms of material waste, time loss, and workflow variability, with limited consideration of human cognitive capacity as a constrained resource (Ballard & Howell, 2003; Koskela, 2000). When human factors are considered, they are often treated as static attributes (e.g., skill level, experience) rather than as dynamic cognitive states that fluctuate within and across tasks. Cognitive waste complements traditional Lean waste categories by representing inefficiencies in mental processing that contribute to defects, delays, and rework. This limits the ability of existing planning and control systems to proactively manage cognitively demanding conditions on a task-level before they manifest as errors, rework, or safety incidents. Consequently, there is a clear gap between (i) the theoretical richness of CLT and its proven explanatory power in other domains, and (ii) the current state of construction research and practice, where cognitive load is rarely operationalized, monitored, or integrated into decision-making frameworks. Addressing this gap requires a structured approach that translates CLT constructs into task-level characteristics and site conditions and embeds cognitive metrics into Lean planning and control mechanisms.

This paper contributes by conceptually operationalizing the integration of Cognitive Load Theory within Lean Construction control systems to provide a structured approach to embedding cognitive considerations into task design and project control. It identifies how cognitive load emerges in construction tasks, how it can be diagnosed and measured, and how it can inform task design, training, and project controls. Beyond diagnostics, the framework highlights the potential of embedding cognitive load into project control systems as a new class of key performance indicators (KPIs). Unlike traditional controls that track cost, schedule, and quality outcomes after the fact, cognitive load indicators provide real-time, task-level insights into human capacity and overload risk. A spike in extraneous load, for example, may serve as an early warning signal of potential rework, delays, or safety incidents. Conversely, balanced intrinsic and germane loads may reflect conditions of optimal learning and flow. Managers can proactively identify “cognitive hotspots,” redesign tasks before errors occur, and continuously improve the alignment between human capacity and task demands by integrating cognitive KPIs into Lean planning and control cycles. This positions cognitive load not only as a

diagnostic tool but also as a predictive control mechanism that complements traditional Lean metrics and strengthens the industry's ability to manage productivity and reliability.

LITERATURE REVIEW

COGNITIVE LOAD THEORY

Cognitive Load Theory (CLT) developed by Sweller, (1988), explains how the limitations of human working memory influence performance and learning during task execution. CLT distinguishes between three types of cognitive load: intrinsic load, which is determined by the inherent complexity of a task; extraneous load, which arises from the way information is presented or from inefficiencies in the task environment; and germane load, which represents the mental effort devoted to learning, schema development, and skill acquisition. According to CLT, performance deteriorates when total cognitive load exceeds available working memory capacity, whereas effective task design aims to reduce extraneous load and manage intrinsic load to support germane load. CLT has been widely applied in educational psychology (Paas et al., 2003; Sweller et al., 2011), instructional design, healthcare (Danner-Schröder & Ostermann, 2020), and human-computer interaction (Bhattacharya & Butail, 2024) to improve learning outcomes and reduce error. In these domains, structured task design, progressive disclosure of information, and feedback mechanisms have been shown to reduce unnecessary cognitive effort and enhance performance. Despite its strong theoretical foundation and successful application in other high-risk, complex environments, CLT has received limited attention in construction management research, particularly at the task and production levels (Eltahan et al., 2025a).

COGNITIVE DEMANDS IN CONSTRUCTION

Construction work is characterized by high levels of uncertainty, variability, and fragmentation, which place significant cognitive demands on workers (Fang et al., 2024). Tasks often require simultaneous processing of visual information, physical coordination, safety awareness, and communication under time pressure (Abdelkhalek et al., 2019; Hamzeh et al., 2019). Research has shown that errors, rework, and safety incidents frequently occur during tasks involving complex information processing, poor coordination, or environmental stressors such as noise, congestion, and interruptions (Abd El-Karim et al., 2017; Agbo et al., 2022). Existing studies in construction have explored workload, fatigue, and attention using subjective assessments, performance measures, and physiological indicators such as eye tracking, heart rate variability, and EEG (Al-Haddad et al., 2022; Elmousalami et al., 2025; Lee et al., 2021). Noueihed & Hamzeh, (2022) advocate for a human-centric vision of Construction 4.0, emphasizing that digital technologies should be designed to support, rather than overwhelm, human cognitive capabilities. These studies demonstrate that construction workers experience fluctuating cognitive demands throughout task execution, and that excessive workload is associated with reduced performance and increased risk. However, much of this research focuses on measuring workload rather than explaining why cognitive overload occurs or how it can be systematically managed through task design and project controls (Eltahan et al., 2025b, 2025d).

EMERGING APPLICATIONS OF CLT IN CONSTRUCTION

Recent advances in digital technologies have created new opportunities to explore cognitive load in construction contexts. Virtual reality (VR), augmented reality (AR), and wearable sensing technologies have been used to study attention, mental workload, and learning during construction tasks (Adami et al., 2022; Alkan & Basaga, 2023; Liu et al., 2024). Some studies have suggested that immersive training environments and visual aids can reduce cognitive burden and improve task performance by simplifying information processing and supporting skill development. Lean Construction research has also emphasized principles such as visual

management, standardization, and flow reliability (Abdelkhalek et al., 2019; Agrawal et al., 2024), which implicitly align with CLT's objective of reducing extraneous cognitive load. However, these connections are rarely made explicit, and cognitive load is not formally integrated into Lean planning or control systems. As a result, cognitive considerations remain largely disconnected from production management practices. Overall, while elements of CLT are beginning to appear implicitly in construction research through training, simulation, and workload measurement, a systematic framework that links cognitive load diagnosis, monitoring, intervention, and control within Lean Construction remains missing. This gap motivates the development of the framework proposed in this paper.

METHODOLOGY

This study follows a Design Science Research (DSR) methodology developed by Offermann et al., (2009). The research is structured around three core stages: problem identification, artifact design and development, and evaluation. First, for problem identification, a structured review of research in construction management, cognitive psychology, and Lean Construction was conducted to identify how productivity, rework, and human factors have been addressed to date. Construction productivity research has traditionally focused on process inefficiencies, rework, and resource constraints, with limited explicit consideration of workers' cognitive capacity during task execution. While human factors and workload have been widely studied in domains such as aviation, healthcare, and manufacturing, their systematic integration into construction planning and control remains underdeveloped. Existing construction studies often rely on indirect workload proxies or post-hoc assessments, limiting their usefulness for real-time decision-making. This gap motivates the need for a theory-grounded, operational framework that enables practitioners to (i) diagnose sources of cognitive load at the task level, (ii) measure cognitive demand using objective and subjective indicators, and (iii) embed cognitive considerations into Lean project controls. Addressing this need aligns with Lean Construction's emphasis on waste reduction and flow reliability, while extending it to explicitly account for human cognitive limitations. Second, artifact design and development, insights from CLT were translated into the construction context by mapping intrinsic, extraneous, and germane load to task-level characteristics and site conditions. This process is grounded in Lean concepts of waste and flow, conceptualizing extraneous load as a form of waste that disrupts value creation. A four-step framework was designed to manifest CLT in construction practice: (i) diagnosing load sources, (ii) monitoring load with objective, subjective, and behavioural indicators, (iii) intervening in task design to optimize load, and (iv) integrating cognitive metrics into Lean project controls. Finally, for evaluation, the framework was iteratively refined through discussions with industry practitioners and academic experts. Practitioners included three senior managers with over 15 years of industry experience, whose feedback informed the evaluation process by confirming the practical relevance of the framework and highlighting the current lack of structured methods for incorporating cognitive considerations into task design. To demonstrate applicability, the framework was applied to the task of cutting fiberglass cable trays in a modular electrical yard. This task was selected because it combines precision requirements, safety considerations, and coordination challenges, making it representative of high cognitive demand in construction workflows. The case demonstration was used to highlight how cognitive load sources can be systematically diagnosed, measured, and controlled, and how cognitive metrics can function as predictive KPIs within Lean planning systems. The case presented in this study serves as an illustrative demonstration of the framework's applicability rather than empirical validation.

PROPOSED FRAMEWORK

This study proposes a four-step framework that links diagnosis, monitoring, intervention, and control. The framework is designed to translate CLT principles into actionable strategies that align with Lean Construction's focus on reducing waste and enhancing flow. The framework synthesizes theoretical principles and empirical observations into a coherent, task-level decision artifact consistent with an abductive design logic. Step 1 involves mapping the sources of intrinsic, extraneous, and germane load within tasks. Step 2 focuses on monitoring cognitive load in practice through objective, subjective, and performance-based indicators. Step 3 introduces targeted interventions to reduce extraneous load, optimize intrinsic load, and support germane load. Finally, Step 4 embeds cognitive metrics into Lean controls, establishing new key performance indicators (KPIs) and enabling early detection of cognitive hotspots. The framework is summarized in Figure 1.

STEP 1: MAP COGNITIVE LOAD SOURCES

Identifying cognitive load in construction requires distinguishing between the different sources of demand that tasks impose on workers. Cognitive Load Theory identifies three primary types of cognitive load: intrinsic, extraneous, and germane, and each has unique sources and diagnostic strategies.

Intrinsic Load: Intrinsic load stems from the inherent difficulty of the task itself, such as the number of interacting elements and the level of expertise required. In construction, this may include Complex measurements (e.g., precise cable tray cutting or conduit bending in electrical work), Multiple interdependencies (e.g., coordinating wiring with HVAC and drywall trades in confined spaces), and high-stakes operations (e.g., crane lifts or live electrical connections). Diagnosis of intrinsic cognitive load can be carried out through task decomposition, where activities are broken down into smaller steps to assess the number of interactions and dependencies involved. In addition, expert judgment provides valuable insights by rating the level of complexity and skill demands required for specific tasks. Finally, reviewing the error-proneness history of a task helps identify those that consistently lead to mistakes or rework, which often signals a high intrinsic load.

Extraneous Load: Extraneous load arises from how tasks are organized and the avoidable inefficiencies or distractions that add unnecessary cognitive burden. In construction, this often occurs when workers are forced to interpret ambiguous instructions or drawings, such as unclear dimensions for fiberglass cutting. It may also be caused by environmental distractions, including poor lighting, excessive noise, or cluttered workspaces in a modular yard. Frequent interruptions, such as pausing to confirm specifications, locate missing tools, or resolve conflicting information, further increase the mental effort required to complete even simple tasks. To map extraneous load, several practical methods can be applied. Site observations and checklists help capture recurring issues such as interruptions, noise, or poor layout conditions that disrupt task flow. Worker feedback, collected through short surveys or quick interviews, provides first-hand insights into the factors that slow down or confuse workers. Additionally, document reviews can reveal inconsistencies or unclear specifications in drawings and work packages that create unnecessary mental effort. Together, these approaches allow managers to pinpoint sources of extraneous load and target them for elimination as a form of waste reduction.

Germane Load: Germane load refers to the positive mental effort that workers invest in developing new skills, forming schemas, and improving their long-term efficiency. From a Lean Construction perspective, germane load can be compared to the capacity freed for value-adding activities: when wasteful burdens are reduced, workers' mental resources are redirected toward learning, improving, and performing tasks that enhance flow and value creation. It is also present in skill transfer, when workers apply knowledge gained from training programs or

VR simulations to real-world tasks. Additionally, reflective problem-solving, such as analyzing mistakes or rework episodes to refine future performance, represents valuable cognitive investment. Although germane load supports learning, it must be carefully managed so that the process of acquiring skills does not overwhelm workers during live task execution. Importantly, reducing unnecessary extraneous load and managing intrinsic complexity create cognitive space for germane load, enabling workers to focus on building expertise rather than battling inefficiencies.

Identifying germane load is directly related to monitoring improvements in performance over time, as these gains reflect that workers are developing schemas and freeing cognitive capacity for higher-value activities. When errors decrease, task execution becomes faster, or knowledge is transferred more smoothly from training to practice, it indicates that unnecessary cognitive effort is being reduced and redirected toward productive learning and refinement. It can also be monitored by reviewing training outcomes, such as improvements observed in VR practice sessions or task rehearsal activities. Finally, think-aloud protocols or reflective interviews with apprentices provide insights into how workers internalize knowledge and build cognitive strategies.

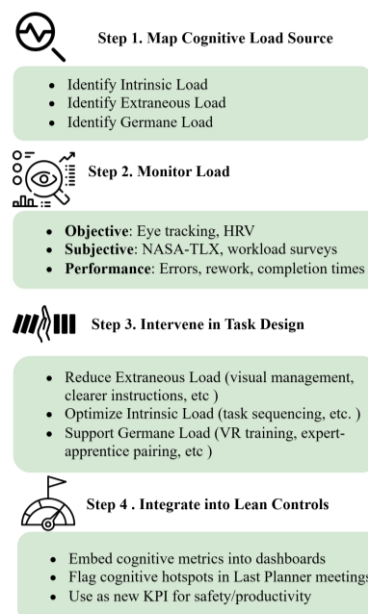


Figure 1: Proposed Framework for Manifesting CLT in Construction

STEP 2: MONITOR COGNITIVE LOAD IN PRACTICE

After identifying potential sources of cognitive load, the next step is to monitor how they manifest during task execution. Monitoring provides real-time or near-real-time feedback that helps managers identify cognitive hotspots before they result in rework, delays, or safety incidents. Unlike diagnosis, which identifies where load is likely to occur, monitoring captures how load is actually experienced by workers on site.

Monitoring cognitive load in practice can be achieved through a combination of objective, performance, and subjective indicators. Objective indicators rely on wearable technologies such as eye-tracking or heart-rate variability (HRV) to detect fluctuations in mental workload. For instance, frequent gaze shifts between drawings and materials during fiberglass cutting may signal that a worker is experiencing high processing demands. These physiological measures provide direct, real-time insights into cognitive strain. Performance indicators focus on observable outputs such as error rates, rework frequency, or cycle times. A sudden increase in miscuts, delays, or material waste may reveal that workers are overloaded and unable to process task demands efficiently. Unlike physiological measures, performance indicators are easily

tracked within existing project control systems and can serve as practical proxies for cognitive load. Subjective indicators complement these methods by capturing workers' self-reported experiences of effort, stress, and frustration. Quick surveys, verbal check-ins, or short forms of established tools like NASA-TLX can be integrated into daily huddles to provide immediate feedback. Although subjective, these indicators give workers a voice in highlighting moments where task demands exceed capacity. The value of monitoring lies in its direct link to Lean control loops. Managers can treat overload as an early warning signal of non-value-adding activities by identifying when workers' cognitive demands are surpassing available capacity. This allows for proactive interventions, such as redesigning instructions, resequencing work, or adjusting staffing, before rework or incidents occur. In this way, monitoring becomes the bridge between diagnosis and intervention, embedding cognitive performance into the continuous feedback and control cycle of construction projects.

STEP 3: INTERVENE TO REDUCE COGNITIVE LOAD

Once cognitive load sources have been identified and monitored in practice, the next step is to intervene by redesigning tasks and work conditions to better align task demands with human cognitive capacity. The goal of intervention is not to eliminate complexity altogether, but to reduce unnecessary cognitive burden, manage unavoidable complexity, and create space for learning and value-adding activities. Interventions are therefore structured around the three types of cognitive load identified by CLT.

Reducing Extraneous Load

Interventions targeting extraneous load focus on eliminating avoidable sources of mental effort that do not contribute to task value. Cognitive waste can be understood within established Lean waste categories, where excessive cognitive load contributes to defects (errors and rework), waiting (delays due to uncertainty or information gaps), and overprocessing (unnecessary mental effort caused by inefficient task design or unclear instructions). In construction, this may include improving the clarity of work instructions and drawings, enhancing visual management practices, and reducing environmental distractions such as poor lighting or cluttered workspaces. For example, providing clearly dimensioned cutting layouts, colour-coded markings, or standardized work instructions can reduce the need for interpretation during fibreglass cutting tasks. From a Lean perspective, reducing extraneous load directly aligns with waste elimination, as it removes non-value-adding cognitive effort that disrupts flow.

Reducing Intrinsic Load

Intrinsic load cannot be removed because it is inherent to the task; however, it can be optimized through task design. Interventions may include breaking complex activities into smaller, manageable steps, sequencing tasks to minimize interdependencies, or assigning work based on skill level and experience. For instance, cutting tasks can be sequenced from simpler components to more complex assemblies, allowing workers to progressively manage task demands. Such strategies help prevent cognitive overload while maintaining task integrity.

Supporting Germane Load

Interventions supporting germane load aim to encourage productive cognitive effort related to learning and skill development. This includes providing opportunities for guided practice, mentorship, and structured training such as VR-based simulations or mock-ups. Importantly, germane load is best supported after extraneous load has been reduced and intrinsic load has been optimized, as this creates the cognitive space necessary for learning. From a Lean Construction perspective, germane load represents the capacity available for continuous improvement and value creation, enabling workers to refine skills, reduce errors over time, and contribute to more reliable production. Together, these interventions translate cognitive load

insights into actionable changes at the task level, ensuring that monitoring results lead to meaningful improvements rather than passive observation. While task-level interventions help reduce cognitive overload and support learning, their impact can be sustained only if cognitive considerations are systematically embedded in project management practices. To move beyond isolated improvements, cognitive load must be incorporated into Lean control mechanisms that guide planning, coordination, and continuous improvement. This motivates the final step of the framework: integrating cognitive load into Lean project controls.

STEP 4: INTEGRATE INTO LEAN PROJECT CONTROLS

The final step of the framework focuses on embedding cognitive load insights into Lean project control systems to support proactive decision-making and continuous improvement. Rather than treating cognitive load as a one-time diagnostic outcome, this step positions it as an operational control variable that complements traditional Lean metrics related to cost, schedule, safety, and quality. Cognitive indicators derived from monitoring activities such as physiological signals, performance trends, and worker feedback can be aggregated and visualized through dashboards or planning tools. They can be operationalized within Lean management systems by integrating them into existing planning and control routines. For example, cognitive indicators such as eye-tracking patterns, heart rate variability (HRV), error rates, and task delays can be used as leading indicators of cognitive strain and performance variability. When tracked over time, these indicators enable teams to identify recurring cognitive hotspots, defined as tasks or work conditions where cognitive demands consistently approach or exceed worker capacity. Integrating cognitive load metrics into planning routines, such as Last Planner meetings or daily huddles, allows teams to act proactively. Tasks identified as cognitively demanding can be revisited in terms of sequencing, resource allocation, work packaging, or training needs before execution. In this sense, cognitive load functions as an early warning indicator, shifting project control from reactive problem-solving to preventive action.

From a performance measurement perspective, cognitive load indicators can be framed as a new class of human-centered key performance indicators (KPIs). Unlike traditional KPIs that assess outcomes after completion, cognitive KPIs provide task-level insight into whether work is being performed under cognitively sustainable conditions. Cognitive load indicators extend existing Lean control practices by providing early signals of variability and waste, consistent with Lean principles of flow reliability, respect for people, and waste reduction. High extraneous load may indicate waste, while stable or improving performance coupled with reduced cognitive strain suggests that capacity is being freed for value-adding activities. Embedding cognitive load into Lean project controls, this framework extends Lean's focus on flow and waste reduction to include the human cognitive system. This integration strengthens the ability of project teams to align task demands with human capacity, enhancing reliability, safety, and productivity across construction workflows.

EVALUATION AND DISCUSSION

CASE DEMONSTRATION: CUTTING FIBERGLASS CABLE TRAYS

To demonstrate the applicability of the proposed framework, this section illustrates how the four-step Cognitive Load Theory (CLT) framework can be applied to the task of cutting fiberglass cable trays in a modular electrical yard. This task was selected because it is common in electrical and modular construction and involves precision and safety considerations. Table 1 summarizes the application of the proposed framework to the fiberglass cutting task.

Step 1: Map Cognitive Load Sources

The first step involves identifying potential sources of intrinsic, extraneous, and germane cognitive load associated with fiberglass cutting. Intrinsic load arises from the precision

required in measuring, marking, and cutting cable trays to meet tight tolerances, as well as from safety considerations related to dust exposure and sharp edges. Extraneous load may stem from unclear drawings, inconsistent dimensions, poor lighting conditions, noise, or frequent interruptions to clarify specifications or locate tools. Germane load is present when apprentices are learning proper cutting techniques, interpreting drawings, or improving their efficiency through repetition and feedback.

Step 2: Monitor Cognitive Load in Practice

Once potential sources are identified, cognitive load can be monitored during task execution using a combination of objective, performance, and subjective indicators. Objective indicators may include wearable-based measures such as eye-tracking or heart-rate variability to detect periods of elevated mental effort, for example when workers repeatedly shift attention between drawings and materials. Performance indicators, such as mis-cuts, material waste, rework, or increased cycle times, can signal moments when cognitive demands exceed capacity. Subjective indicators, collected through brief worker check-ins or short workload surveys, provide additional insight into perceived effort and frustration during the task.

Step 3: Intervene to Optimize Cognitive Load

Based on diagnostic and monitoring insights, targeted interventions can be introduced. Extraneous load can be reduced by providing clearer cutting layouts, standardized instructions, or improved lighting in the modular yard. Intrinsic load can be optimized by sequencing cutting tasks from simpler to more complex components or by assigning tasks according to skill level.

Table 1. Application of the CLT Framework to Fiberglass Cutting in a Modular Yard

Framework Step	Purpose	Application to Fiberglass Cutting Task
Step 1: Map Cognitive Load Sources	Identify cognitive demand	Intrinsic load: precision in measuring, marking, and cutting panels; safety considerations (dust, sharp edges). Extraneous load: unclear drawings, inconsistent dimensions, poor lighting, noise, interruptions to clarify specifications or locate tools. Germane load: learning, interpreting drawings.
Step 2: Monitor Cognitive Load in Practice	Detect cognitive overload during task execution	Objective indicators: eye-tracking or HRV capturing elevated cognitive load (e.g., frequent gaze shifts between drawings and materials). Performance indicators: mis-cuts, material waste, rework, increased cycle times. Subjective indicators: short workload surveys capturing perceived effort.
Step 3: Intervene to Optimize Cognitive Load	Align task demands and cognitive capacity	Reduce extraneous load: clearer cutting layouts, standardized instructions, improved lighting. Optimize intrinsic load: sequence tasks from simple to complex, assign tasks based on skill level. Support germane load: guided practice, mentorship, VR-based rehearsal without production pressure.
Step 4: Integrate into Lean Project Controls	Sustain improvements through planning and control	Review cognitive and performance indicators during planning meetings to flag activities as a potential cognitive hotspot. Enable proactive adjustments in sequencing, staffing, or training applicable to the identified bottleneck. Use cognitive load indicators as human centered KPIs supporting continuous improvement in safety, quality, and productivity.

Germane load can be supported through guided practice, or training activities such as VR-based simulations that allow workers to rehearse cutting procedures without production pressure.

Step 4: Integrate into Lean Project Controls

Finally, insights from the fiberglass cutting task can be integrated into Lean project control systems. Cognitive indicators and performance trends can be reviewed during planning meetings to identify fiberglass cutting as a potential cognitive hotspot. This enables proactive adjustments in task sequencing, staffing, or training before execution. Over time, cognitive load indicators associated with this task can serve as human-centered KPIs, complementing traditional Lean metrics and supporting continuous improvement in safety, quality, and productivity.

CONCLUSION

Construction productivity and reliability are shaped not only by processes and technologies, but also by the cognitive capacity of the workers who execute tasks under dynamic and uncertain conditions. While Lean Construction has made significant progress in improving workflow reliability and reducing waste, the cognitive demands placed on workers remain largely implicit in current planning and control practices. This paper addressed this gap by introducing a framework for manifesting Cognitive Load Theory (CLT) in construction. The proposed four-step framework links diagnosis, monitoring, intervention, and control to translate CLT principles into actionable strategies for Lean Construction. The framework provides a structured way to identify avoidable cognitive waste, manage unavoidable task complexity, and create capacity for learning and value-adding activities. The case illustration of cutting fiberglass cable trays demonstrates the framework's application to routine construction tasks; however, its practical relevance requires validation through empirical application and measurable outcomes. This study contributes to Lean Construction research by reframing cognitive load as a form of waste and positioning cognitive indicators as human-centered key performance indicators that can serve as early warning signals for rework, delays, and safety risks. Rather than reacting to failures after they occur, the framework enables a proactive approach to aligning task demands with human capacity, supporting flow, reliability, and continuous improvement. The framework presented in this study is conceptual and illustrated through a hypothetical case, which represents a limitation. Moreover, the illustrative nature of the case does not include analytical comparison or empirical evidence demonstrating how cognitive metrics directly influence planning, control, or performance outcomes. Future research will focus on systematic field implementation and validation across multiple construction contexts to examine the feasibility of integrating cognitive metrics into existing Lean control systems and explore how digital technologies such as wearables and immersive training environments can support cognitive-aware planning and control. Construction projects can move toward more human-centred, resilient, and productive systems by integrating cognitive load diagnostics in lean construction.

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REFERENCES

- Abd El-Karim, M. S. B. A., Mosa El Nawawy, O. A., & Abdel-Alim, A. M. (2017). Identification and assessment of risk factors affecting construction projects. *HBRC Journal*, 13, 202–216. <https://doi.org/10.1016/j.hbrcj.2015.05.001>

- Abdelkhalek, E. S., Elsibai, M. D., Ghosson, G. K. & Hamzeh, F. R. (2019). Analysis of Visual Management Practices for Construction Safety. *Proc. 27th Annual Conference of the International Group for Lean Construction (IGLC)* (pp. 1069–1080). <https://doi.org/10.24928/2019/0175>
- Adami, P., Rodrigues, P. B., Woods, P. J., Becerik-Gerber, B., Soibelman, L., Copur-Gencturk, Y., & Lucas, G. (2022). Impact of VR-based training on human–robot interaction for remote operating construction robots. *Journal of Computing in Civil Engineering*, 36(3), 04022006.
- Agbo, E. A., Izam, Y. D., & Ayegba, C. (2022). Quantifying the Impact of Work Environment Factors on the Variability of Labour Productivity in Wall Plastering. *Journal of Construction in Developing Countries*, 27, 109–125. <https://doi.org/10.21315/jcdc-01-21-0009>
- Agrawal, A. K., Zou, Y., Chen, L., Abdelmegid, M. A., & González, V. A. (2024). Moving toward lean construction through automation of planning and control in last planner system: A systematic literature review. *Developments in the Built Environment*, 18, 100419. <https://doi.org/10.1016/j.dibe.2024.100419>
- Akanmu, A., & Okoukoni, F. (2018). Swarm nodes for automated steel installation tracking: A case study. *Automation in Construction*, 90, 294–302. <https://doi.org/10.1016/j.autcon.2018.01.011>
- Al-Haddad, S., Sears, M., Alruwaythi, O., & Goodrum, P. (2022). Complexity, Performance, and Search Efficiency: An Eye-Tracking Study on Assembly-Based Tasks among Construction Workers (Pipefitters). *Buildings*, 12. <https://doi.org/10.3390/buildings12122174>
- Alkan, I. B., & Basaga, H. B. (2023). Augmented reality technologies in construction project assembly phases. *Automation in Construction*, 156. <https://doi.org/10.1016/j.autcon.2023.105107>
- Ballard, G., & Howell, G. (2003). Lean project management. *Building Research & Information*, 31(2), 119–133. <https://doi.org/10.1080/09613210301997>
- Barbosa, F., Woetzel, L., & Mischke, J. (2017). Reinventing construction through a productivity revolution. *McKinsey & Company*. <https://www.mckinsey.com/capabilities/operations/our-insights/reinventing-construction-through-a-productivity-revolution>
- Bhattacharya, A., & Butail, S. (2024). Measurement and Analysis of Cognitive Load Associated with Moving Object Classification in Underwater Environments. *International Journal of Human–Computer Interaction*, 40(10), 2725–2735. <https://doi.org/10.1080/10447318.2023.2171275>
- Danner-Schröder, A., & Ostermann, S. M. (2020). Towards a Processual Understanding of Task Complexity: Constructing task complexity in practice. *Organization Studies*, 43 (3) <https://doi.org/10.1177/0170840620941314>
- Elmousalami, H., Hui, F. K. P., & Aye, L. (2025). Electroencephalography (EEG) for psychological hazards and mental health in construction safety automation: Algorithmic Systematic Review (ASR). *Automation in Construction*, 177, 106346. <https://doi.org/10.1016/j.autcon.2025.106346>
- Eltahan, A., Lee, G., & Hamzeh, F. (2025a). A human-centered framework for assessing task complexity in construction: A cognitive load perspective. *Engineering Construction & Architectural Management*. <https://doi.org/10.1108/ECAM-04-2025-0585>
- Eltahan, A., Lee, G., & Hamzeh, F. (2025b). Exploring Cognitive Load and Task Complexity in Dynamic Tracking Tasks: Insights for Construction Workflows. *International Symposium on Automation and Robotics in Construction (ISARC) Proceedings, 2025 Proceedings of the 42nd ISARC, Montreal, Canada*, 532–539. <https://doi.org/10.22260/ISARC2025/0070>

- Eltahan, A., Lee, G. & Hamzeh, F. (2025c). Feasibility of Eye-trackers for Monitoring Cognitive Load in Lean Construction 4.0. In Seppänen, O., Koskela, L., & Murata, K. (Eds.), *Proceedings of the 33rd Annual Conference of the International Group for Lean Construction (IGLC 33)* (pp. 892–904). <https://doi.org/10.24928/2025/0141>
- Eltahan, A., Lee, G., & Hamzeh, F. (2025d). From Theory to Construction: Rethinking Task Complexity and Cognitive Load. *Joint CSCE Construction Specialty & CRC Conference 2025*, Montreal, Canada.
- Fang, X., Yang, X., Xing, X., Wang, J., Umer, W., & Guo, W. (2024). Real-Time Monitoring of Mental Fatigue of Construction Workers Using Enhanced Sequential Learning and Timeliness. *Automation in Construction*, 159. <https://doi.org/10.1016/j.autcon.2024.105267>
- Görsch, C., Lappalainen, E., Malvik, T. O., Lehtovaara, J., & Riekk, J. (2025). From Theory to Practice: Applying Time Span of Discretion in Last Planner System® and Takt Production to Navigate Work Complexity. In *Proceedings of the 33rd Annual Conference of the International Group for Lean Construction (IGLC 33)* (Vol. 33, pp. 37-47). IGLC. <https://doi.org/10.24928/2025/0299>
- Hamzeh, F. R., Faek, F., & AlHussein, H. (2019). Understanding improvisation in construction through antecedents, behaviours and consequences. *Construction Management and Economics*, 37(2), 61–71. <https://doi.org/10.1080/01446193.2018.1497189>
- Jebelli, H., Ahn, C. R., & Stentz, T. L. (2016). Comprehensive Fall-Risk Assessment of Construction Workers Using Inertial Measurement Units: Validation of the Gait-Stability Metric to Assess the Fall Risk of Iron Workers. *Journal of Computing in Civil Engineering*, 30(3), 04015034. [https://doi.org/10.1061/\(ASCE\)CP.1943-5487.0000511](https://doi.org/10.1061/(ASCE)CP.1943-5487.0000511)
- Koskela, L. (2000). An exploration towards a production theory and its application to construction. *Technical Research Centre of Finland*. <https://aaltoodoc.aalto.fi/items/076e4e0b-d86b-4171-b205-a68e85af8bd6>
- Lee, G., Choi, B., Jebelli, H., & Lee, S. (2021). Assessment of construction workers perceived risk using physiological data from wearable sensors: A machine learning approach. *Journal of Building Engineering*, 42. <https://doi.org/10.1016/j.jobbe.2021.102824>
- Liu, C., González, V. A., Lee, G., Cabrera-Guerrero, G., Zou, Y., & Davies, R. (2024). Integrating the Last Planner System and Immersive Virtual Reality: Exploring the Social Mechanisms Produced by Using LPS in Projects. *Journal of Construction Engineering and Management*, 150(7), 04024070. <https://doi.org/10.1061/JCEMD4.COENG-14430>
- Noueihed, K., & Hamzeh, F. (2022). Envisioning a Human Centric Approach to C4.0 Technologies. *Lean Construction Journal*. *Lean Construction Journal (LCJ)*.
- Offermann, P., Levina, O., Schönherr, M., & Bub, U. (2009, May). Outline of a design science research process. In *Proceedings of the 4th International Conference on Design Science Research in Information Systems and Technology* (pp. 1-11).
- Paas, F., Tuovinen, J. E., Tabbers, H., & Van Gerven, P. W. M. (2003). Cognitive Load Measurement as a Means to Advance Cognitive Load Theory. *Educational Psychologist*, 38(1), 63–71. https://doi.org/10.1207/S15326985EP3801_8
- Rasouli, M., Karimi, H., & Hatami, J. (2025). Reconstructing construction safety Training: A systematic review based on learning theories and instructional design principles. *Safety Science*, 184. <https://doi.org/10.1016/j.ssci.2024.106769>
- Sweller, J. (1988). Cognitive Load During Problem Solving: Effects on Learning. *Cognitive Science*, 12(2), 257–285. https://doi.org/10.1207/s15516709cog1202_4
- Sweller, J. (2011). Cognitive load theory. In *Psychology of learning and motivation* (Vol. 55, pp. 37-76). Academic Press.