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WIP: The Impact of Early versus Late STEM Exposure on Cognitive Load in First Year Undergraduate Engineers: A Scoping Review

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Introduction

Efforts to expand science, technology, engineering, and math (STEM) degree attainment have accelerated in recent decades in response to increasing workforce demands [1, 2]. One of these efforts includes the development of numerous programs and initiatives designed to provide early STEM exposure targeting K-12 students, such as summer camps, advanced courses, and robotics clubs [3-5]. These efforts have been shown to boost students' STEM interest [6], increase enrollment and persistence in STEM degree programs [7], and enhance students' self-efficacy and preparedness during their first year of college [8, 9]. These pre-college experiences often involve hands-on and collaborative activities that allow students to apply STEM concepts, fostering both technical skills and self-efficacy [10]. Previous studies highlight the benefits of early STEM engagement in both formal and informal learning environments, suggesting that students' preparation for undergraduate engineering is closely tied to the types and availability of pre-college opportunities they have access to.

Not all students enter undergraduate engineering with pre-college or early exposure to STEM. Structural inequities such as school resources result in unequal access to advanced STEM coursework and extracurricular activities before entering college – particularly for low-income or under-resourced schools [11, 12]. This can influence who enters engineering and the level of preparation they bring with them. For example, students in lower-income schools may not be afforded access to calculus-based physics, making them ineligible for certain engineering programs [13]. Consequently, first-year engineering students begin their undergraduate education with highly variable levels of prior STEM engagement, often due to factors such as socioeconomic status, school resources, access to advanced coursework, and the availability of extracurricular STEM opportunities [14]. While differences in pre-college STEM exposure are well-documented, much less is known about how these differences translate into students' cognitive experiences once they enter first-year engineering classrooms. Beyond shaping interest and future engagement in STEM, these experiences also contribute to the development of foundational problem-solving strategies that may influence how students process new engineering course content.

A critical but underexplored lens for understanding how students' backgrounds shape their experiences in education is cognitive load. Cognitive Load Theory (CLT), developed by John Sweller in the late 1980s, posits that human working memory has a limited capacity and that overload hinders learning [15]. Working memory temporarily stores and manipulates information needed for complex cognitive tasks [16], and when its capacity is exceeded, cognitive overload occurs, impeding learning regardless of a learner's motivation or ability [17]. Viewing learning through the lens of cognitive load shifts attention from individual student characteristics and deficit language to the learning process based on the interaction between instructional approaches and learners' prior knowledge.

Most educational research connects student learning to prior knowledge, including the seminal work by Vygotsky on the Zone of Proximal Development (ZPD) [18]. Vygotsky defined the

ZPD as the difference between what a student can do independently, and what they can do with some help from someone more capable [19]. At the root of this concept is a student's prior knowledge. Sweller found that a learner's intrinsic cognitive load is influenced both by the inherent complexity of the material and by the learner's existing prior knowledge [20]. Paas and Sweller later found that individuals with prior knowledge often hold relevant schemas in long-term memory, allowing them to treat multiple interacting elements as a single cognitive unit. This process reduces strain on working memory and enables them to manage complex material more efficiently. In contrast, students without such schemas must process each element as novel, rapidly consuming working memory resources and increasing the likelihood of overload, slower progress, or frustration [21]. A student's cognitive load can have major implications on their engineering education experience and outcomes.

Elevated cognitive load has been linked to poorer performance on engineering tasks [20-22], particularly in situations where students lack sufficient prior knowledge and instructional support is minimal [23]. For example, research shows that when novices engage in problem solving without worked examples, they must rely on insufficient strategies, which imposes high cognitive load [24]. Students who enter college with prior STEM exposure may draw on existing schemas to manage this complexity, while students without such exposure must process each element as novel, increasing the risk of cognitive overload [25]. Cognitive load is not inherently detrimental; rather, inequities arise when students are asked to engage with complex material without the schemas to properly manage that complexity. If a student did not have early STEM exposure and thus lacked opportunities to practice similar problem-solving, they may find engineering tasks more demanding than peers who had the opportunity to practice problem solving in similar contexts. As a result, cognitive load provides a useful lens for examining why students with similar abilities may experience different learning trajectories in introductory engineering courses.

Pre-college STEM exposure and cognitive load in engineering have each been extensively studied, but they have largely been examined in isolation. Therefore, this paper presents a scoping literature review that maps the overlap of existing scholarship on pre-college STEM exposure and cognitive load to identify research gaps and inform equitable instructional design for first-year engineering programs, guiding future research.

Methodology

For this work, a scoping literature review method was used. There exists a wide range of literature review types and methods, each with small differentiations in their primary goal and method [26]. A scoping review is characterized by a goal of identifying the nature and extent of existing research evidence for a particular topic, focusing on the themes and gaps in the literature. This method is distinct from a systematic literature review [27] in that it does not focus closely on inclusion and exclusion criteria to identify all relevant work in the area of interest, nor does it have a formal quality assessment [26].

Scoping Review Protocol

This review draws upon the methods outlined by Arksey and O'Malley [28] to describe the current state of research and identify gaps for future work. Their review process involves five stages: (1) identifying research questions, (2) developing a search strategy, (3) selecting studies, (4) charting relevant data, and (5) summarizing and reporting findings. Although presented in a linear fashion, the work is, in practice, much more iterative. The purpose of this scoping literature review is to assess the extent to which pre-college STEM exposure and cognitive load have been jointly examined in undergraduate engineering education and to identify gaps at their intersection that limit understanding of variation in first-year student learning experiences.

Stage 1: Identify the Research Questions

Based on existing literature, the research questions guiding this study are:

1) How is the relationship between early STEM exposure and cognitive load in undergraduate engineering represented in the existing literature?

2) What gaps exist in the literature regarding how cognitive load is experienced by students in undergraduate engineering programs with early versus late STEM exposure?

It is important to define or operationalize vague terms in the research questions. Early STEM exposure is operationalized here to mean any form of formal or informal exposure and includes Advanced Placement (AP) or International Baccalaureate (IB) courses in math and science; middle or high school STEM curriculum programs; extracurriculars like robotics, coding clubs, or math competitions; and/or pre-college engineering programs like summer camps or research internships. On the other hand, students with late exposure are those who took only basic high school math and science courses; had little to no involvement in STEM-related extracurricular activities; and entered undergraduate engineering with limited formal or informal STEM learning experiences. This operationalization reflects how pre-college STEM exposure is commonly conceptualized in the literature, while also acknowledging that exposure varies in intensity, duration, and quality – something that is addressed in the findings.

Stage 2: Develop Search Strategy

To be as comprehensive as possible in identifying possible relevant studies, searching for research evidence was performed across different sources, including electronic databases, key journals, and conference proceedings. For scoping limitations, only studies published between 2000 and 2025 were considered in this review. Additionally, studies published in a language other than English were excluded. Finally, the “first year” aspect of undergraduate engineering was intentionally dropped from search terms due to the limited number of findings. However, the focus of the larger study will remain on the first-year undergraduate engineering context. The selection process began with creating a list of critical search terms. Compiling search terms was an iterative process, with terms being added and removed as the results emerged. This iterative approach is suggested by several guiding papers on scoping literature review methods [28-30]. Following the methods used in Fernandez et al. (2023), tables showing the central search terms and the additional inclusion criteria for selecting studies are included below [31].

Searches were conducted in major bibliographic databases (Compendex, Scopus, ERIC, PsycINFO, Web of Science) and supplemented with targeted searches of publisher platforms (Taylor & Francis, Wiley Online Library). The search timing was between December 2025 and January 2026 and performed using Boolean operators with each of the combinations of terms related to cognitive load, engineering education, and pre-college STEM experiences listed in Table 1. While repositories such as ASEE PEER and Google Scholar were not formally included due to their limitations in search refinement, they were referenced to identify relevant papers that were not captured in the other database searches.

Hand searching, or searching through specific journals for articles that may have been missed from a database search [32], was also performed in the following journals, identified from the Engineering Education Publication Venues list compiled in the Engineering Education Community Resource [33]: Journal of Engineering Education, Studies in Engineering Education, and Advances in Engineering Education. For each journal, the table of contents, article titles, and abstracts were reviewed for issues published between 2000 and 2025 to identify relevant studies that may not have been retrieved through database searches. These engineering specific journals were chosen instead of broader STEM education journals to maintain the focus on engineering and is recognized as a study limitation.

Table 1. Central Inclusion Criteria

Central Inclusion Criteria	Working Definition	Synonyms (OR Search Terms)
Cognitive load	The amount of working memory capacity used to process complex and novel information in a learning environment [25]	Mental workload, working memory, cognitive effort, mental effort. *For a discussion on the distinction between these, see [34]*
Engineering	The group of college majors related to engineering	Engineering education, undergraduate engineering, post-secondary engineering, college engineering
Pre-college STEM experiences	Educational experiences (formal or informal) around STEM that occurred before entering college	Prior knowledge, STEM exposure, STEM knowledge, early STEM, pre-college STEM

Table 2. Additional Inclusion Criteria

Additional Criteria	Working Definition	Rationale	Implementation
Publication Type	Journal manuscript or conference publication	Restricted to peer reviewed papers for validity [35]	Database search restriction
Publications from the 21st century	Dates ranging from January 1, 2000, to the search date (with continuous new searching during writing phase)	A time constraint provides bounding to reflect changes since ABET's Engineering Criteria 2000 [36]	Database search restriction
US institutions	Institutions (including colleges and universities) within the United States	Limits review to be of higher relevance to a US context of study	Observed during screening
Written in English	Publication available in English	Author's limitation and resources constraints	Database search restriction

Stage 3: Study Selection

Papers that met the eligibility criteria were then examined for relevance based on their titles and abstracts. Any obviously irrelevant results were excluded, with the rest moving on to a more complete screening. Many studies that were initially displayed after reviewing titles and/or abstracts were deemed irrelevant for this review. Some common reasons for studies being excluded include studies performed outside the US, not involving engineering, and not focused on undergraduate students. The remaining studies were then subjected to full-text screening to confirm their focus on pre-college STEM exposure, cognitive load, and engineering education.

Stage 4: Charting Relevant Data

Stage 4 of the Arksey and O'Malley framework involves charting key information from included studies. In this review, no studies met all inclusion criteria combining pre-college STEM exposure, cognitive load, and undergraduate engineering. As a result, formal data charting was not conducted. However, a charting tool was developed in advance, including variables related to study design, participant characteristics, measures of cognitive load, and operationalizations of pre-college STEM exposure. The inability to populate this charting tool underscores a critical gap in the literature, and this absence of intersecting studies is therefore treated as a primary finding of the review.

Findings

Stage 5: Summarizing and Reporting Findings

Because searches that simultaneously combined the relevant topics did not yield any studies that met the inclusion criteria, the findings presented here draw on the constructs independently. Early analysis of the literature reveals consistent themes within each, but a lack of intersecting findings. This reinforces the need for future work that explicitly links pre-college STEM exposure to cognitive load in first-year undergraduate engineering. As this work is ongoing, subsequent stages of the scoping review will continue to refine search strategies to ensure comprehensive findings.

Themes in Pre-College STEM Exposure Literature

The types and availability of pre-college STEM exposure, both formal and informal, have grown in recent decades [37]. Common programs include robotics clubs, structured K-12 STEM curricula, summer programs, and outreach initiatives led by colleges and universities. One of the most prevalent K-12 STEM curricula is Project Lead the Way, which incorporates project-based learning to teach the engineering design process [38-40]. Ortiz and colleagues found that out of school experiences such as FIRST robotics have a positive impact on STEM identity and a feeling of community [41]. Across these contexts, the literature consistently reports on the perceived benefits of participation, including improved professional skills, increased comfort with the engineering design process, and heightened self-efficacy and interest in pursuing engineering [8, 42]. Notably, these studies typically emphasize participation outcomes rather than the specific content knowledge students develop through these experiences. This emphasis is consequential because, without understanding the specific knowledge and problem-solving schemas students develop through these experiences, it remains unclear how pre-college STEM exposure translates into differences in cognitive load when students encounter complex engineering tasks.

As shown through the examples given above, much of existing work on the outcomes of pre-college STEM exposure emphasizes affective or motivational outcomes, with limited attention to learning outcomes related to knowledge application and transfer once students reach undergraduate engineering. When quantitative outcomes of program participation are reported, they are typically focused on persistence or major declaration, rather than direct measures of learning outcomes or cognitive processes [37]. As a result, while prior STEM exposure is shown to be beneficial for those entering undergraduate engineering, the ways in which it influences students' early learning experiences remains underexplored.

Additionally, knowledge building as an outcome of pre-college STEM exposure has been minimally studied (for exceptions, see [43, 44], although they are not assessing a particular pre-college experience). There are, however, several possible explanations for why this is the case. McCarthy and colleagues showed that prior knowledge is not easily observable or quantifiable because it includes multiple dimensions including amount, accuracy, specificity, and coherence – each of which affect performance differently [45]. A bibliometric study by Bittermann and colleagues showed that relatively little research explores the types of prior knowledge because it is difficult to measure and characterize [46]. Thus, knowledge stemming from pre-college STEM exposure is often treated as a binary (e.g. participated or did not participate), ignoring the duration, quality, and intensity of these experiences. It is difficult to assess the impact of each activity on students' knowledge acquisition without more in-depth investigation. This binary classification may hide some nuance of the effect of different types of prior STEM exposure and therefore limit the ability to examine how early STEM exposure translates into differential learning outcomes once students encounter complex engineering coursework.

Themes in Cognitive Load in Engineering Education

Cognitive load theory has been used in multiple research areas, including cognitive science and education, as well as in several professional domains, such as healthcare [47] and aviation [48]. Within engineering contexts, cognitive load has informed instructional design in areas such as problem solving [49] and engineering design tasks [50]. Cognitive load is particularly salient in first-year engineering contexts, where students are often simultaneously learning unfamiliar content, disciplinary language, and applying previous knowledge in a new context [51]. Despite its demonstrated relevance to complex, technical learning environments, such as undergraduate engineering, cognitive load remains relatively underutilized as a lens for examining variation in students' learning experiences across different educational backgrounds.

Cognitive load has been measured using a variety of subjective and objective approaches. Self-report measures remain among the most common approaches to measuring cognitive load in research, with one of the first being the NASA Task Load Index (NASA-TLX). This measure focuses on perceived workload [52] and had early applications in flight simulation – to investigate differences between self-reporting scales and a physiological measure [53] and ICU nursing – in assessing its reliability for measuring overall workload [54]. Another measure includes the 9-point Paas scale, which is now one of the most widely used subjective measures for self-reporting in educational context. It asks respondents to rate their mental effort (seen as an index of cognitive load) from very, very low to very, very high [23]. In their experimental study on just-in-time information presentation for troubleshooting tasks, Kester et al. (2006) measured learners' invested mental effort using the Paas 9-point subjective rating scale, demonstrating its sensitivity to instructional design differences that affected cognitive load [55]. While this and other self-report measures are valuable for capturing learners' perceptions of mental effort, they primarily reflect retrospective or aggregate experiences and may not capture moment-to-moment fluctuations in cognitive demand or the effects of unconscious processing [56]. These findings indicate the wide range of ways cognitive load can be assessed through self-reporting.

In response to the limitations of self-report measures, researchers have increasingly explored physiological indicators as proxy measures of cognitive load. While electrodermal activity (EDA) does not directly measure cognitive load, it captures physiological arousal associated with mental effort and task engagement [57]. Other notable physiological proxy measures of cognitive load include electroencephalography (EEG) [58], heart rate variability [59], and pupil dilation [60]. For example, EEG has been used to distinguish levels of cognitive workload during complex problem-solving tasks by analyzing alpha and theta brain waves, which are sensitive to task difficulty [58]. Heart rate variability has similarly been employed as a physiological proxy for cognitive load, with reductions in HRV associated with increased mental effort during demanding learning and simulation-based tasks [59]. Finally, larger pupil diameters have been shown to indicate increased task difficulty [60]. These approaches allow for more fine-grained, time-sensitive analysis of cognitive demand during complex activities. This methodological diversity reflects the field's recognition that no single measure fully captures cognitive load, and that triangulation across self-report and physiological indicators may be necessary for robust assessment.

Cognitive load theory is positioned to illuminate the mechanisms through which instructional design and learners' prior knowledge jointly shape learning outcomes, which offers not just a description of who struggles, but why. Unlike frameworks centered on motivation or identity, CLT directs attention to the cognitive architecture underlying task performance, specifically how working memory capacity is allocated, exceeded, or efficiently managed during learning [61]. This process-level focus makes it particularly useful for examining what happens cognitively when students with different educational histories encounter the same engineering tasks.

Discussion

This early-stage scoping review indicates that while pre-college STEM exposure and cognitive load are each well-studied in engineering education, little work has examined how these constructs intersect in first-year undergraduate engineering contexts. This gap likely reflects a disciplinary divide: research on pre-college STEM exposure has been conducted primarily in education research and program evaluation, where affective outcomes take precedence over cognitive processes. Cognitive load research, on the other hand, has developed largely within cognitive psychology and instructional design, with limited understanding of how students' educational histories shape their working memory. The result is that cognitive processing has remained an underexplored mechanism for understanding why students with similar academic abilities may experience introductory engineering coursework differently. First-year engineering is a well-documented attrition point, particularly for students from marginalized racial groups and first-generation students [62-64]. If cognitive load is a mechanism through which differential exposure shapes performance, its identification provides a target for intervention.

This divide also had methodological implications: pre-college STEM research has relied mainly on surveys, participation records, and academic outcomes, while cognitive load research employs self-report scales and physiological measures. Integrating these traditions will require deliberate methodological alignment, which the proposed dissertation research is positioned to address. Self-report measures such as the Paas scale can capture perceived mental effort, but as retrospective and aggregate instruments, they may not detect moment-to-moment fluctuations in cognitive load. Physiological indicators including EDA, EEG, heart rate variability, and pupil dilation offer continuous, time-sensitive data but, as this review reveals, have not been applied in contexts that account for students' pre-college educational backgrounds. Developing a multimodal measurement approach may be necessary to capture the full range of cognitive effects and to triangulate across the limitations of any single measure.

These findings carry implications for both research and instructional practice. If cognitive load varies systematically with the type and quality of students' pre-college STEM exposure - not merely their academic ability - then instructional supports in first-year engineering should be designed with this variation in mind. For students who enter without substantial prior STEM schemas, reducing extraneous cognitive load through worked examples and scaffolded problem sets may be particularly important in the early weeks of coursework. More broadly, this review surfaces a body of cognitive load research that has received limited uptake in engineering education, despite its demonstrated relevance to complex technical learning environments. Bringing CLT into conversation with pre-college exposure literature and engineering education more broadly offers a framework for explaining, rather than merely describing, observed variation in first-year engineering experiences.

Several limitations are acknowledged. As a scoping review, this work does not include formal quality appraisal of included studies, a recognized trade-off of the method [24]. Restricting the review to US-based, English-language publications and to hand-searching only engineering-specific journals may have excluded relevant work from adjacent fields including cognitive psychology, broader STEM education, and health professions education, where cognitive load measurement is well developed.

As a work in progress, this scoping review establishes the absence of research that directly integrates pre-college STEM exposure and cognitive load in undergraduate engineering. The next phase of this work will involve completing the scoping review to fully chart and synthesize findings from studies that separately examine pre-college STEM exposure and prior knowledge in engineering and examine cognitive load in engineering education. Findings from the completed scoping review will inform the continued development of the dissertation, examining how differences in pre-college STEM exposure relate to cognitive load during first-year engineering tasks.

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