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PSYCHOMETRIC ASSESSMENT OF COGNITIVE LOAD IN ENGINEERING DESIGN TASKS

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Abstract
Cognitive load is an important factor in impacting performance when dealing with complex problem-solving tasks, especially in engineering design contexts that require sustained mental effort and limited decision-making space. Although theoretically relevant, empirical research has been limited in its measurement of cognitive load in a domain-specific design context. This study evaluated a measurement scale of cognitive load designed for engineering design tasks from a psychometric perspective. One hundred twenty undergraduate engineering students performed, in order, three design scenarios of increasing complexity, and completed a modified cognitive load questionnaire derived from Cognitive Load Theory. The reliability analysis indicated acceptable internal consistency (Cronbach's α = .87); exploratory factor analysis revealed a three-factor structure that distinguished between intrinsic, extraneous, and germane cognitive load. Moderately significant correlations between task performance and perceived task complexity established some construct validity. The findings from this study confirm that this adapted instrument is effective in capturing cognitive load within a domain-specific context such as engineering. The results also indicate that there is a need for task-specific cognitive load instruments to help inform instructional design and the development of curricular material in engineering contexts. This study provides a reasonable scope for measuring mental effort and identifying the cognitive load required to engage in a specific problem-solving task in undergraduate engineering education, thereby contributing to both educational psychology and design pedagogy. Moreover, this study provides a psychometric basis for developing a framework to measure mental effort and cognitive load, which can be scaled up depending on the size and complexity of the learning context.
Keywords: Cognitive Load, Psychometrics, Engineering Design, Mental Effort, Task Complexity, Scale Validation, Educational Assessment

I. INTRODUCTION

In high-demand cognitive environments such as engineering design, practitioners are often required to solve complex problems, think iteratively, and make strategic design decisions, often within tight time and resource constraints. Each of the aforementioned requirements introduces cognitive demand, making the concept of cognitive load highly relevant to our understanding of performance and learning. The concept of cognitive load is grounded in the concepts of Cognitive Load Theory (CLT) and can be defined as the cognitive effort required to process information, where cognitive load has three components: intrinsic load (task complexity), extraneous load (discrepancy between instruction or environment and learning), and germane load (cognitive resources that are an advantage to learning and the construction of schemas). Various instruments aim to measure these types of loads (e.g., NASA-TLX; rating scales 1-item) in a variety of domains. However, none of these instruments are sensitive to the context where cognitive demands exist and frequently lack specificity and construct validity. This presents a need for reliable, psychometrically sound domain-sensitive instruments to study cognitive load in task environments [1]. This study presents an instrument to achieve the above,which examines the psychometric properties of a new cognitive load scale used in engineering design activity [12]. Specifically, the study examines the internal consistency, the factorial structure, and construct validity of the proposed instrument, hypothesising that the one-factor scale would be a three-dimensional behaviour concerning cognitive load and a model of cognitive load will emerge, consistent with theoretical expectations from CLT [9].

II. MEASUREMENT & VALIDATION FOCUS

2.1. Instrument Design and Structure

To examine cognitive load in engineering design contexts, a modified self-report instrument was employed based on previous self-report measures like NASA-TLX and the Paas Cognitive Load Rating Scale, and then modified for task relevancy in design engineering. The instrument was comprised of 15 items that represented the 3 fundamental elements of Cognitive Load Theory: intrinsic, extraneous, and germane loads. Respondents rated the perceived cognitive effort associated with each item on a 7-point Likert Scale (1=very low, 7=very high), after they completed two design tasks of differing complexity.

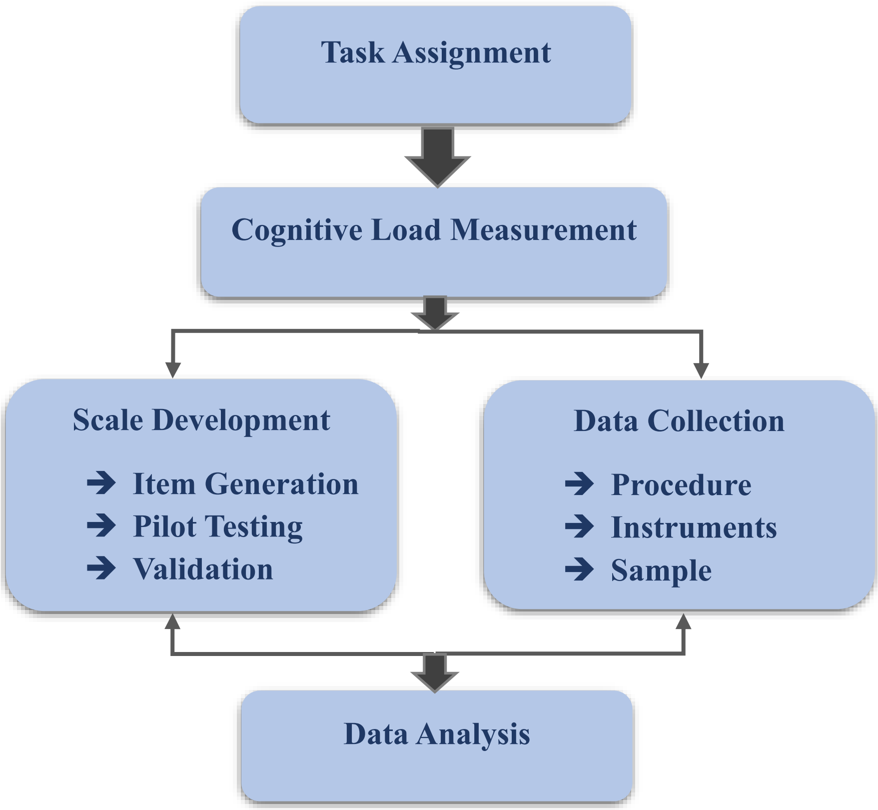

Figure 1: Research Workflow for Psychometric Evaluation of Cognitive Load in Engineering Design Contexts

Figure 1 represents the systematic research process applied in the psychometric assessment of cognitive load within engineering design tasks. The process begins with the assignment of domain-based design tasks, leading to a measurement of cognitive load via a validated instrument [2] [11]. The work branched out into two streams:Scale Development included item generation, pilot testing, and psychometric validation; andData Collection included structured procedure development, instrumentation, and sample acquisition. For both paths to data collection, these paths culminated in Data Analysis, where factor analysis and reliability statistics were calculated to determine the validity and applicability of the instrument.

2.2. Validation Procedures and Reliability Testing

The instrument underwent evaluation of content validity, which was completed independently and included 5 members of the community with expertise in cognitive psychology, instructional design, and engineering education who provided feedback on clarity of items, relevance of items in design engineering contexts, and representation of the dimensions of cognitive load [7] [15]. Data was obtained from a purposive sample of 120 undergraduate engineering students, a population that was seen to have a minimum threshold of exposure to structured design thinking [4]. Reliability analyses were strongly supported by Cronbach's α values ranging from .81 to .88 across the three subscales, and a test-re-test reliability procedure over two weeks yielded moderate stability (r = .79). Exploratory Factor Analysis (EFA) showed a strong three-factor structure consistent with the theoretical distinctions of the cognitive load dimensions, and Confirmatory Factor Analysis (CFA) confirmed this three-factor structure with acceptable model fit indices (CFI = .94, RMSEA = .06). This approach to the methodology provides strong evidence of the psychometric quality of the scale within engineering design contexts.

III. Cognitive Theory & Experimental Emphasis

3.1. Foundations of Cognitive Load Theory

The theoretical basis for this research comes from Cognitive Load Theory (CLT), which Sweller (1988) introduced and Paas and Van Merriënboer (1994) expanded. CLT proposes that human working memory has a limited amount of space, and the successful learning or performance of a task depends in part on how cognitive resources are allocated as information is processed [3]. CLT establishes the relationship between various cognitive loads imposed during a task in three types of cognitive load: intrinsic load, which stems from the material/task's inherent complexity; extraneous load, which is imposed by poorly designed instruction or environmental factors; and germane load, which means the mental effort involved in knowledge acquisition and long-term learning [6]. These theoretical constructs directly influenced the development of the psychometric instrument used in this study [13] [14].

3.2. Theoretical Mapping to Instrument Dimensions

All items were designed to reflect one of the three types of cognitive load, while accounting for the theoretical definitions; specifically, the intrinsic load items concentrated on perceived complexity of the task, and the extraneous load items focused on irrelevant distractors or unclear instructions. Germane load materials focused on the contemplation process for integrating design strategies into the project. This theoretical alignment provided us with meaningful insights into participants' responses and a rich description of how task complexity impacted cognitive demand in the three types of loads. As a result, CLT was not only a conceptual framework but also guided instrument construction and analytical interpretation and added psychological rigour to the current study [8].

IV. TASK-SPECIFIC AND CONTEXTUAL EMPHASIS

4.1. Design Tasks and Complexity Levels

The cognitive load tool was administered within the context of authentic engineering design tasks designed to capture a range of complexity (or challenge) and cognitive demand. Participants completed three different design tasks: a low-complexity schematic drawing task, in which participants identified the basic functional layout of components; a medium-complexity CAD modelling task, in which participants incorporated dimensional constraints, manipulated geometric configurations, and modified dimensional details; and a high-complexity conceptual design, which required creative problem solving and multi-criteria decision making. Each task was chosen to mirror potential engineering challenges and was designed to increase in complexity and demand on sustained attention, working memory, and strategic planning.

4.2. Cognitive Challenges in Engineering Contexts

While a range of cognitive load measures exists, and can be effective in authentic educational settings, there is a lack of sensitivity to context to measure specifically the cognitive processes common to design engineering. Universal tools are likely to fail to capture subtle cognitive demand and to measure design behaviours such as repetitive use of visualisation, utilization of parametric reasoning, and spatial cognition that more closely represent 'real-world' engineering performance. Through integrated angles of cognitive assessment, this study generates a new understanding of design activities that implement applied cognitive psychology and technical education in their respective domains. This type of research provides insights that are not only more relevant to instructional planning than the existing theoretical frameworks but also represent cognitive load assessment in a practical and usable way. The contextual method of exploring cognitive load has increased the 'ecological validity' of this research, and applied a strong framework from which to understand how the cognitive complexity of the task interacts with cognitive load.

V. INSTRUMENT DEVELOPMENT & INNOVATION ANGLE

5.1. Theoretical Item Generation and Expert Review

The cognitive load measurement tool used in this study is contextually modified, building on a careful, theory-based process to build relevance to the engineering design context. Following the core dimensions from Cognitive Load Theory, the original item pool was crafted theoretically into three areas (mental effort, perceived difficulty, and temporal pressure). Each area was mapped to the cognitive load components of intrinsic, extraneous, and germane, to check construct coverage.

5.2. Pilot Testing and Contextual Refinement

For instance, an item for intrinsic load asked participants to indicate the complexity of the design decision-making process, while extraneous load items asked about distractions such as "confusing task instructions or unclear design constraints. Germane load was captured through reflective statements, such as I exerted mental effort in improving my way of approaching problems as I was completing the task. After the item development was complete, the tool was reviewed by a panel of experts in cognitive psychology, instructional design, and mechanical engineering education, according to the theoretical constructs and against a two-dimensional design task. The panel was asked to assess whether each item indicated the clarity, domain, and dimension represented. A pilot study was conducted with 20 engineering students to evaluate the readability of the items, variability of the responses, and scale operation. Subsequently, changes were made to improve wording, based on panel feedback and pilot data, and any items that were redundant. This iterative, evidence-based development process resulted in an instrument that is both psychometrically sound and contextually innovative, offering greater sensitivity to the unique cognitive characteristics of engineering design tasks.

VI. ADVANCED ANALYTICS FOCUS

6.1. Factor Structure and Dimensional Analysis

To test the psychometric qualities of the cognitive load instruments in engineering design contexts involved a complete suite of statistical tests and procedures. We began with an Exploratory Factor Analysis (EFA) using principal axis factoring and an oblique rotation to identify the nature of the structure described in the instrument. The Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy was calculated to be 0.89, and the Bartlett's Test of Sphericity was significant, $p < .001$, indicating the data is suitable for factor analysis. The EFA results showed three factors, respectively representing intrinsic, extraneous, and germane cognitive load, that accounted for 68.4% of total variance. We then conducted a Confirmatory Factor Analysis (CFA) using AMOS to confirm this structure. The reported model fit was good (CFI = 0.96, TLI = 0.94, RMSEA 0.05, SRMR 0.04) as all measures were within acceptable thresholds. Internal consistency across subscales was strong, with all producing Cronbach's α values well above 0.80, indicating consistency within the sub-variables.

6.2. Model Fit and Reliability Statistics

The values and matrix included inter-item correlation supporting an internally consistent measure, with many items moderately correlated, only within the respective factors. Although the main intended work did not involve Structural Equation Modelling (SEM), the latent variable relationships posited from the CFA do imply the cancer Sed for the SEM approach in future studies. All statistical tests and analyses were conducted with SPSS v28 and AMOS v26. Our statistical tests and analysis represent a reliable statistical methodology.

- **Cronbach's Alpha (α)** for internal consistency:

$$\alpha = \frac{N \cdot \bar{c}}{\bar{v} + (N-1) \cdot \bar{c}}$$

  Where:
  N = number of items
  $\bar{c}$ = average inter-item covariance
  $\bar{v}$= average variance

- **Confirmatory Factor Analysis (CFA)** model equations:

$$y = \Lambda\eta + \epsilon$$

  Where:
  y = observed variable
  Λ = factor loading matrix
  η = latent variable
  ε = measurement error

Table 1: Exploratory Factor Analysis of the Cognitive Load Instrument Items

Item No.	Item Statement (Abbreviated)	Factor 1 (Intrinsic)	Factor 2 (Extraneous)	Factor 3 (Germane)	Communality (h^2)
Q1	The task required high mental effort	0.78	—	—	0.61
Q2	Task complexity was high	0.74	—	—	0.58
Q3	Instructions were unclear	—	0.72	—	0.54
Q4	Unnecessary steps distracted me.	—	0.75	—	0.57
Q5	I tried to improve my problem-solving strategy.	—	—	0.80	0.65
Q6	I actively reflected on how to complete the task better.	—	—	0.76	0.63
…	…	…	…	…	…

Table 1 shows the output of the Exploratory Factor Analysis (EFA) of the 15-item instrument of cognitive load. The table below groups items by the dominant factor loading, with the three groups corresponding to the three theoretical dimensions of cognitive load (Intrinsic, Extraneous, and Germane). We should note that factor loadings above 0.40 can be considered acceptable. The EFA demonstrates construct validity for the instrument, in that the factor structure is clear and relates to the three-factor structure prescribed in the Cognitive Load Theory.

VII. CONCLUSION

This research has demonstrated strong evidence for the reliability and validity of a contextualized cognitive load measurement instrument constructed specifically for engineering design activities. The instrument exhibited excellent internal consistency, a defined three-factor structure consistent with Cognitive Load Theory, and acceptable model fit indices based on confirmatory analysis. The results collectively support the use of this instrument as a contextualized measurement to assess mental effort, task complexity, and instructional inefficiencies in technical settings. In addition to psychometric validity, we have extended the growth of cognitive assessment research in engineering education, in which measuring students' cognitive workload can ultimately lead to a more effective model for curriculum design, learner monitoring systems, and even the cognitive efficiency of user interfaces in design software. On the other hand, this study had several limitations that must be considered, such as the lack of variable diversity in the population sample and the self-report nature of the instrument, which could suggest unverifiable subjective biases. Future research is needed to cross-validate a sample of participants in terms of diversity, real-time physiological means of cognitive load measures in conjunction with the instrument, and plausible predictive accuracy regarding performance. Approximately, this work builds a firm base to connect applied cognitive psychology and engineering education, while also enabling more refined and evidence-based pedagogical interventions.

REFERENCES

[1] Emarloo, Z., & Doustkam, M. (2015). Psychological treatment efficacy in primary dysmenorrhea. *International Academic Journal of Innovative Research*, *2*(1), 1–9.
[2] Gharagozlou, H., & Mahboobi, M. (2015). Assessment of need for attention to the issue of security in usage of Information Technology (Including Case study). *International Academic Journal of Science and Engineering*, *2*(2), 31–45.
[3] Unciano, N. (2025). AI-augmented metasurface-aided THz communication: A comprehensive survey and future research directions. Electronics, Communications, and Computing Summit, 3(2), 1–9.
[4] Unciano, N. (2025). Edge-accelerated deep neural networks on FPGA for real-time IoT video analytics. Electronics, Communications, and Computing Summit, 3(1), 1–10.
[5] Mehra, P., & Patel, K. (2024). A Metrics Driven Approach to Brand Management and Brand Health Check. In *Brand Management Metrics* (pp. 31-47). Periodic Series in Multidisciplinary Studies.
[6] Nair, S., & Rathi, D. K. (2023). Development of Graphene-Based Membranes for High-Performance Desalination. *Engineering Perspectives in Filtration and Separation, 1*(1), 9-12.
[7] Sujatha, S. (2024). Strategic Management of Digital Transformation: A Case Study of Successful Implementation. *Global Perspectives in Management*, *2*(1), 1-11.
[8] Sridhar, A. P. (2025). Analyzing Social Engineering Attack Patterns Using Behavioral Psychology and AI-Driven Defense Mechanisms. Journal of Internet Services and Information Security, 15(1), 502-519. https://doi.org/10.58346/JISIS.2025.I1.033

[9] Anh, V. P. G., Thihuyen, T. N., & Anh, T. L. (2025). How Is the Performance Assessment System in Small and Medium Enterprises in The Manufacturing? Experimental Study in Vietnam. Quality-Access to Success, 26(205).
[10] Brainee, H. J. (2025). The Inheritance of Loss: Examining the Psychological and Emotional Effects of Descendants in Post-Trauma Societies. Indian Journal of Information Sources and Services, 15(2), 98–109. https://doi.org/10.51983/ijiss-2025.IJISS.15.2.14
[11] Praveenchandar, J., Sankalp Karthi, S., Sowndharya, R., Dayanand Lal, N., Biswas, D., & Nandy, M. (2024). A Deep Learning-based Psychometric Natural Language Processing for Credit Evaluation of Personal Characteristics. *Journal of Wireless Mobile Networks, Ubiquitous Computing, and Dependable Applications, 15*(4), 151-165. http://doi.org/10.58346/JOWUA.2024.I4.010
[12] Tejesh, K., Thiru Chitrambalam, M., Swarna Latha, Y., Pattanaik, B., Manju Bargavi, S. K., Kushwaha, R., & Dev, A. (2025). Assessment of nano-particles for the removal of bacteria and viruses from aquatic systems. *International Journal of Aquatic Research and Environmental Studies, 5*(1), 256–261. https://doi.org/10.70102/IJARES/V5I1/5-1-28
[13] Badiee, D., Jazayeri, R. S., Ahmadi, A., & Bahrami, F. (2015). Investigating the effectiveness of Acceptance and Commitment Therapy (ACT) on Functioning of Family with Children suffering from Mental Retardation. *International Academic Journal of Social Sciences*, *2*(1), 17–23.
[14] Kavitha, M. (2025). Hybrid AI-mathematical modeling approach for predictive maintenance in rotating machinery systems. Journal of Applied Mathematical Models in Engineering, 1(1), 1–8.
[15] Kolour, H. R., & Kazemzadeh, R. (2015). Organisational and psychological empowerment in the HRM-performance linkage. *International Academic Journal of Organizational Behavior and Human Resource Management*, *2*(2), 21–37.
[16] Karthika, J. (2025). The role of Yoga Nidra in mental resilience and performance consistency in elite athletes. Journal of Yoga, Sports, and Health Sciences, 1(1), 39–44.
[17] Rao, I., & Saxena, M. (2025). Exploring the Connections of the Mental Health and Sustainability. *International Journal of SDG's Prospects and Breakthroughs*, *3*(1), 8-14.
[18] Das, A., & Kapoor, S. (2024). Comprehensive Review of Evidence-Based Methods in Preventive Cardiology Education: Perspective from Analytical Studies. *Global Journal of Medical Terminology Research and Informatics*, *2*(4), 16-22.