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Mapping cognitive load profiles in realistic mathematics education: A study with aerospace engineering students

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Abstract

Although Realistic Mathematics Education (RME) promotes deeper conceptual learning, empirical evidence mapping different types of cognitive loads in university engineering mathematics is limited. This mixed-methods study profiled intrinsic, extraneous, and germane cognitive loads among 76 first-year aeronautical engineering students working on RME-based task, a contextualized double integral problems modelling aircraft wing surface. We measured load components with a CLT questionnaire that adapted from Leppink et.al and mental effort with the Paas scale, then triangulated findings with student reflections and observations. Correlations showed intrinsic and germane load related to students' mental effort, while extraneous load was minimal, suggesting clear task design. Multiple regression analysis clarified that the germane load was the main unique predictor of mental effort, whereas intrinsic complexity and extraneous factors contributed little uniquely. Qualitative data confirmed that students used strategies such as breaking tasks into sub-steps, activating prior knowledge, and peer explanation to manage effort. We propose an RME–CLT alignment framework that scaffolds intrinsic difficulty, minimizes extraneous processing, and cultivates germane engagement through reflective context-rich tasks. The findings also inform the design of cognitively efficient engineering-mathematics curricula. Thus, it offers practical guidance for designing cognitively efficient engineering mathematics instruction and recommends future studies using longitudinal and real-time measures.

Keywords: aerospace engineering; cognitive load theory; engineering mathematics; mental effort; realistic mathematics education

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Introduction

Mathematics is a fundamental pillar of engineering education, providing the abstract reasoning and quantitative analysis skills necessary for solving complex real-world problems. However, traditional approaches to mathematics instruction in higher education often prioritize procedural fluency and theoretical abstraction over contextual understanding, potentially disengaging students from the practical applications of mathematics in their professional fields. Realistic Mathematics Education (RME) reframes mathematics as a human activity situated in authentic contexts and has demonstrated consistent benefits in K–12 settings while also showing potential in higher education (Gravemeijer & Doorman, 1999; Juandi et al., 2022). In simultaneously, applications of Cognitive Load Theory (CLT) in university STEM show that education that decreases unnecessary load while scaffolding intrinsic complexity improves learning efficiency (Goold & Devitt, 2020; Mayer & Moreno, 2016; Santoso & Sari, 2025).

In parallel, Cognitive Load Theory (CLT) offers a complementary framework for optimizing learning efficiency by managing intrinsic, extraneous, and germane cognitive loads (Mayer & Moreno, 2016; Paas et al., 1994; Sweller, 1988, 2011). Evidence from STEM education indicates that instruction which reduces unnecessary processing while scaffolding intrinsic complexity enhances conceptual learning and transfer (Goold & Devitt, 2020; Jong, 2010; Kalyuga, 2006). Integrating RME and CLT therefore provides a promising pathway to balance realism with cognitive manageability in advanced mathematics instruction.

Despite these theoretical alignments, research directly combining RME and CLT in university-level engineering mathematics remains limited. Recent studies in engineering education highlight that engaging with abstract mathematical concepts can impose high cognitive demands (Goold & Devitt, 2020; Juandi et al., 2022). Misalignment between task complexity and learners' cognitive capacity can lead to overload, whereas realistic contexts may enhance meaning-making but increase intrinsic complexity. The CLT framework helps mitigate this tension by managing intrinsic load (IL), minimizing extraneous load (EL), and fostering germane load (GL) to support schema construction.

However, no prior study has simultaneously measured all three CLT load types, intrinsic, extraneous, and germane, within RME-based tasks in university-level engineering mathematics, especially in the aerospace domain. Addressing this gap requires understanding how realistic contexts shape cognitive load distribution and how instructional design can optimize mental effort for effective learning.

In this study, RME was operationalized for Calculus II through a didactical design research (DDR) approach grounded in the emergent model principle (Gravemeijer, 1994). Students engaged in an aerospace engineering task involving the estimation of an aircraft wing's surface area using double integrals, a context demanding conceptual reasoning, visualization, and model interpretation. This design extends RME beyond its K–12 roots, illustrating how contextual modelling can deepen conceptual engagement in advanced engineering mathematics. The study aims to map cognitive load profiles across RME-based learning and propose a practical RME-CLT alignment framework for cognitively efficient, context-driven mathematics instruction in engineering education.

Methods

This study used a mixed-methods design to gain a comprehensive understanding of students' cognitive responses during RME based instruction. Quantitative and qualitative approaches were integrated to enable data triangulation and deeper interpretation. The participants were 76 first-year aerospace engineering students enrolled in Calculus II at a private institute in Yogyakarta during the 2024/2025 academic year, all of whom had completed at least one prior mathematics course. These participants represented the entire cohort registered in the course; hence, no random sampling was applied. While this complete sampling minimized voluntary bias, the absence of randomization may limit the generalizability of findings beyond the studied cohort.

The quantitative phase employed two validated instruments: the Paas Mental Effort Rating Scale (Paas et al., 1994) and the cognitive load theory (CLT) Questionnaire adapted from Leppink et al. (2013). The latter was translated into Indonesian and back-translated to ensure conceptual equivalence, followed by pilot testing with 25 engineering students to assess clarity and reliability. Cronbach's α values indicated acceptable internal consistency for each subscale: Intrinsic Load (α = 0.685), Extraneous Load (α = 0.762), and Germane Load (α = 0.83) as shown in figure 4. The 15-item, 5-point Likert CLT instrument measured IL, EL, and GL, while the Paas scale captured overall mental effort. Four open-ended prompts captured reflections on task difficulty, learning outcomes, and time/effort management, distributed via Google Forms after each RME task.

The RME session consisted of a single application-oriented task lasting approximately 2.5 hours, replacing part of regular exercise time while maintaining syllabus alignment. The task (Figure 1) asked students to use a double integral to estimate the surface area of an aircraft wing section, linking calculus computation with aerodynamic interpretation.

Sebuah bagian kecil dari permukaan sayap pesawat dimodelkan dengan persamaan
A section of an aircraft wing is modeled by

$$z(x,y) = 0.02x^2 + 0.03y, \quad 0 \le x \le 2,\ 0 \le y \le 4$$

where x and y are in meters.
dengan x dan y dalam meter.

Gunakan **integral lipat dua** untuk menghitung **luas permukaan** bagian sayap tersebut.
Use a double integral to estimate the surface area of the wing section.

$$S = \iint_R \sqrt{1 + \left(\frac{\partial z}{\partial x}\right)^2 + \left(\frac{\partial z}{\partial y}\right)^2}\, dA$$

Figure 1. RME task to mapping the CLT

Students worked in small groups of 3–4 to encourage collaborative reasoning typical of RME classrooms. Collaboration guidelines emphasized joint problem solving while ensuring individual accountability through follow-up reflections. The questionnaire administration occurred immediately after task completion to minimize recall bias. In addition, students responded to four open-ended reflection prompts on task difficulty, learning outcomes, and time–effort management. Qualitative data from classroom observations, semi-structured interviews, and reflective journals were thematically analysed to interpret quantitative trends.

Multiple linear regression in SPSS v.26 examined the unique contributions of IL, EL, and GL to mental effort (MERS). Semi-partial correlations quantified each predictor's unique variance. Integration of both data strands provided a multidimensional profile of cognitive load patterns, informing the design of an adaptive and contextually relevant framework for engineering mathematics instruction.

The research adhered to the institutional research ethics guidelines of the host university. As the study involved minimal risk and normal classroom activities, formal administrative approval served as ethics clearance, and all participants provided informed consent prior to data collection. No identifying information was recorded, and confidentiality was maintained throughout the study.

Results

The results are presented by cognitive load component. As shown in Table 1, Items 1–5 measured IL, Items 6–10 measured EL, and Items 11–15 measured GL. Item 16 (Paas) measured overall subjective mental effort (MERS) to complement IL and EL interpretation.

Table 1. Presents the categorization of the questionnaire instruments

No	Categorize	Item Numbers	Description
1	Intrinsic Load (IL)	1, 2, 3, 4, 5	Inherent complexity and demands of the learning task
2	Extraneous Load (EL)	6, 7, 8, 9, 10	Unnecessary mental effort from poor instructional design
3	Germane Load (GL)	11, 12, 13, 14, 15	Conscious effort to integrate, elaborate, and reflect
4	Mental Effort Rating Scale (MERS)	16	Total subjective mental effort (Paas scale)

Descriptive Statistics

	N	Minimum	Maximum	Mean	Std. Deviation
Rata2_IL	76	3.00	5.00	3.9079	.49471
Rata2_EL	76	1.00	4.00	2.4868	.70225
Rata2_GL	76	2.00	5.00	4.0658	.66001
MERS	76	2.00	5.00	4.2632	.83855
Valid N (listwise)	76				

Figure 2. Descriptive statistics

As summarized in Figure 2, students reported relatively high intrinsic load (M = 3.91, SD = 0.49) and germane load (M = 4.07, SD = 0.66), but lower extraneous load (M = 2.49, SD = 0.70), indicating that the RME task was cognitively demanding yet instructionally clear. The overall mental effort (MERS) was moderate to high (M = 4.26, SD = 0.84), suggesting that students invested substantial but manageable cognitive effort during the learning activity.

Validity and reliability check for factor analysis

KMO and Bartlett's Test

Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.730
Bartlett's Test of Sphericity	Approx. Chi-Square	426.654
	df	105
	Sig.	.000

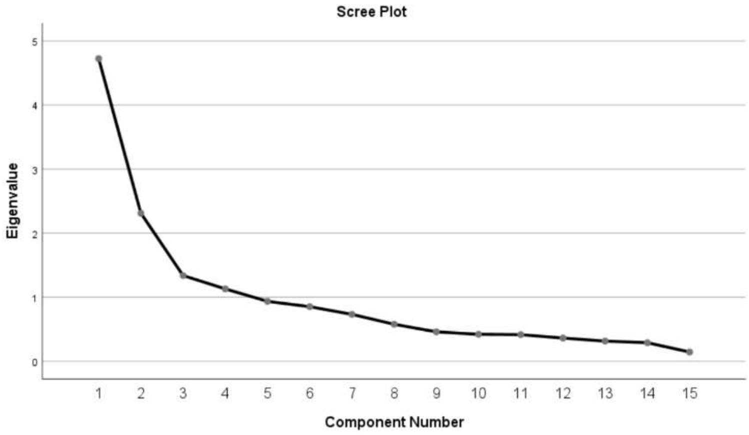

Figure 3. KMO analysis results

To ensure the validity of conducting factor analysis, the Kaiser-Meyer-Olkin (KMO) measure was calculated, yielding a value of 0.730, which falls into the “middling” category (0.70 – 0.79) according to Kaiser’s interpretation as seen in figure 3 above. This indicates that the sample size is adequate for factor analysis. Bartlett’s Test of Sphericity was significant ($X^2(105) = 426.65, p < .001$), confirming item intercorrelation. The eigenvalue analysis yielded three components exceeding 1.0 (4.725, 2.311, and 1.337), explaining 55.82% of the total variance, and the scree plot showed a clear elbow after the third factor (Figure 3). These results confirm a three-factor solution consistent with CLT, representing intrinsic, extraneous, and germane load dimensions.

The factor analysis shows that the cognitive load of aerospace engineering students in RME-based mathematics tasks can be grouped into three dimensions: IL, EL and GL, aligning with CLT and confirming the validity of the adapted Leppink et al. (Leppink et al., 2013) instrument. Overall, the three-factor solution supports theory and offers practical guidance: match task complexity to prior knowledge, reduce extraneous elements, and design activities that promote meaningful learning.

Reliability Statistics

Cronbach's Alpha	N of Items
.685	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
IL1	16.0132	4.253	.342	.673
IL2	15.7368	3.343	.570	.572
IL3	15.5921	3.605	.517	.601
IL4	15.8421	3.628	.419	.646
IL5	15.1842	3.966	.359	.669

(a)

Reliability Statistics

Cronbach's Alpha	N of Items
.762	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
EL1	10.5000	6.360	.581	.705
EL2	10.1184	6.106	.571	.705
EL3	10.5000	5.400	.633	.679
EL4	10.5132	6.493	.428	.754
EL5	9.2632	6.436	.456	.745

(b)

Reliability Statistics

Cronbach's Alpha	N of Items
.830	5

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Cronbach's Alpha if Item Deleted
GL1	15.9342	6.142	.533	.822
GL2	16.1842	6.126	.581	.809
GL3	15.9605	5.132	.774	.751
GL4	16.0921	5.338	.638	.795
GL5	16.4079	5.791	.625	.797

(c)

Figure 4. Reliability analysis results, (a) IL, (b) EL and (c) GL

Based on the reliability analysis results on figure 4, all items met the corrected item–total correlation threshold (> 0.30). Cronbach's α coefficients indicated good internal consistency, supporting the instrument's reliability for this population.

Correlation of cognitive load theory (CLT)

IL versus MERS

Correlations

		MERS	Rata2_IL
MERS	Pearson Correlation	1	.284*
	Sig. (2-tailed)		.013
	N	76	76
Rata2_IL	Pearson Correlation	.284*	1
	Sig. (2-tailed)	.013	
	N	76	76

*. Correlation is significant at the 0.05 level (2-tailed).

Figure 5. Correlation Analysis Results (IL vs MERS)

The first analysis examined the relationship between intrinsic load (IL) and perceived mental effort (MERS). The statistical test indicated a significant correlation on figure 5 ($p = 0.013 < 0.05$), although the effect size was small ($r = 0.284$), suggesting that the practical influence of IL on overall mental effort is limited. This result implies that while the inherent complexity of mathematical tasks and the number of interacting elements contribute to cognitive load, their impact on mental effort is relatively modest. Student reflections and observation notes clarify this pattern: a recurring theme was task decomposition, with many students reporting that "breaking the problem into smaller steps made the task manageable." Others described prior-knowledge activation, stating that linking new tasks to familiar calculus concepts reduced confusion. These patterns imply that although RME problems involve inherent conceptual complexity, learners often deploy metacognitive strategies that attenuate the practical effect of IL on overall effort.

EL versus MERS

Correlations

		MERS	Rata2_EL
MERS	Pearson Correlation	1	-.017
	Sig. (2-tailed)		.886
	N	76	76
Rata2_EL	Pearson Correlation	-.017	1
	Sig. (2-tailed)	.886	
	N	76	76

Figure 6. Correlation analysis results (EL vs MERS)

The second analysis examined the relationship between extraneous load (EL) and perceived mental effort (MERS). The correlation was negative but negligible (r = –0.017) and statistically non-significant (p = 0.886 > 0.05) see figure 6, indicating EL had little measurable impact on total cognitive load. Classroom observations and students' reflections offer two explanations: many participants reported clear problem statements and useful diagrams, one student wrote, "the realistic problems made the math feel closer to real engineering", and EL scores showed little variability, which may reflect consistently well-designed tasks or limited instrument sensitivity. Together, these findings suggest RME tasks minimized extraneous processing, although measurement limits should be acknowledged

GL versus MERS

Correlations

		MERS	Rata2_GL
MERS	Pearson Correlation	1	.378**
	Sig. (2-tailed)		.001
	N	76	76
Rata2_GL	Pearson Correlation	.378**	1
	Sig. (2-tailed)	.001	
	N	76	76

**. Correlation is significant at the 0.01 level (2-tailed).

Figure 7. Correlation analysis results (GL vs MERS)

The third analysis examined germane load (GL) versus perceived mental effort (MERS; see Figure 7). The correlation was significant but modest (r = 0.378, p = .001), indicating that students' deliberate integration and reflection relate to higher mental effort but do not dominate it. Interview excerpts and journals illustrate this germane processing, students reported model building, reflective explanation, and peer discussion (e.g., "working in teams helped me focus on key steps," and "relating problems to aircraft contexts made me think more about why the solution works"). These findings align with Cognitive Load Theory (Sweller, 2011), which links germane processing to schema construction, while noting that other factors (prior knowledge, task interactivity) also contribute to overall effort.

Multiple regression analysis

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change	Durbin-Watson
1	.408[a]	.167	.132	.78119	.167	4.806	3	72	.004	1.927

a. Predictors: (Constant), Rata2_GL, Rata2_EL, Rata2_IL

b. Dependent Variable: MERS

Figure 8. Multiple regression analysis model summary

A multiple regression analysis was conducted to assess the unique effects of IL, EL and GL on perceived mental effort (MERS) see figure 7 & 8. The overall model was significant, F(3,72) = 4.81, p = .004, explaining 16.7% of the variance in MERS (Adjusted R^2 = .132).

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.	Correlations Zero-order	Correlations Partial	Correlations Part	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	1.268	.921		1.376	.173					
	Rata2_IL	.244	.207	.144	1.179	.242	.284	.138	.127	.778	1.285
	Rata2_EL	.120	.134	.100	.896	.373	-.017	.105	.096	.923	1.083
	Rata2_GL	.429	.158	.338	2.709	.008	.378	.304	.291	.744	1.344

a. Dependent Variable: MERS

Figure 9. Multiple Regression Predicting Mental Effort (MERS) from Load Components

Among the predictors on figure 9, only germane load significantly predicted mental effort (β = .338, t = 2.71, p = .008), uniquely explaining 8.5% of the variance ($part^2$ = .085). Intrinsic (β = .144, p = .242) and extraneous load (β = .100, p = .373) loads were non-significant. Although the model accounted for a modest proportion of variance, this is expected in complex cognitive settings where unmeasured factors, such as prior knowledge, mathematics anxiety, or working-memory capacity, also influence mental effort (Kalyuga, 2007; Sweller, 2011).

The non-significant IL effect, despite the task's conceptual complexity, likely reflects the effectiveness of scaffolding and students' compensatory strategies, such as task decomposition and activation of prior knowledge, observed qualitatively. These behaviors may have attenuated the perceived impact of intrinsic load by distributing effort across sub-steps.

Reflection data showed that students who described breaking problems into smaller steps or collaborating on subtask explanations generally reported lower IL and higher GL scores, whereas those expressing confusion about formulas or limits showed slightly higher MERS ratings. This convergence confirms that metacognitive regulation in RME contexts reduces intrinsic strain and enhances germane processing, consistent with CLT principles.

Implications for instructional framework

Table 2 summarizes the proposed RME–CLT framework, which was developed directly from the tasks implemented in this study. Each design principle reflects how cognitive load was managed during the Calculus II RME session. For example, the RME task (Figure 1) represented the enhancement of germane load through contextual reflection linking surface area computation to aerodynamic efficiency. The management of intrinsic load was addressed through progressive sequencing, starting from basic derivatives to applied differential equations, while extraneous load was minimized through clear diagrams and structured worksheets. Together, these strategies demonstrate how RME-based instruction operationalized Cognitive Load Theory in a real aerospace engineering classroom.

Table 2. Proposed RME–CLT framework (Calculus in Aerospace Engineering)

Cognitive Load Principle	Framework Strategy	Concrete Example in Aerospace Context
Enhance Germane Load	Use context-rich, reflective activities	Students compute the surface area of a rectangular wing panel using a double integral and discuss how curvature coefficients affect aerodynamic lift efficiency.
Manage Intrinsic Load	Progressive task sequencing & scaffolding	Students first review partial derivatives, then apply them to construct and evaluate the double integral for the wing surface model.
Minimize Extraneous Load	Clear, concise instructional design	Students follow a guided worksheet with structured steps and clear diagrams to perform the double integral calculation without redundant information.

By systematically aligning these empirically validated design components, the proposed framework enhances cognitive efficiency, deepens conceptual understanding, and reinforces the professional relevance of mathematics learning in engineering contexts.

Discussion

The regression analysis revealed that GL was the only significant positive predictor of MERS, while IL and EL were not significant. However, the effect size was modest ($\beta = 0.338$; $R^2 = 0.167$), indicating that GL contributed meaningfully but not dominantly to the overall variance. This suggests that while constructive cognitive engagement shaped students' mental effort, other unmeasured factors, such as prior knowledge, working-memory capacity, and motivation, likely influenced cognitive load distribution.

Compared with previous studies where intrinsic load often exerts the strongest effect among novice learners (Aditomo, 2014; Du et al., 2023; Gupta & Zheng, 2020; Klepsch & Seufert, 2020), the current results highlight a different pattern. Here, GL's relatively stronger influence may reflect participants' developing engineering identity, contextual task relevance, and metacognitive maturity. These students were not pure novices; they had prior exposure to applied calculus and could activate schema and strategies such as decomposition and reflection, core components of self-regulated learning (Zimmerman, 2010), that channeled cognitive effort toward meaning-making rather than struggling with task complexity. The RME context, linking calculus to an aircraft wing model, may have further promoted germane processing by aligning abstract mathematics with engineering reasoning.

The proposed RME – CLT framework (Table 2) advances existing cognitive load design principles by explicitly integrating contextual realism and guided reinvention into load management strategies. Whereas classical CLT frameworks (Mayer & Moreno, 2016) or expertise reversal models (Kalyuga, 2007) emphasize adaptive load adjustment based on learner expertise, the current model extends these ideas to the RME paradigm, where intrinsic complexity is introduced through authentic contexts but regulated via scaffolding and reflection. This integration offers a concrete pathway to translate CLT principles into discipline-specific, context-driven instruction for engineering mathematics.

Limitations must be acknowledged. First, the study's cross-sectional design restricts causal inference; longitudinal or experimental approaches would better capture how cognitive load evolves across multiple RME cycles. Second, reliance on self-report measures may introduce bias, as CLT questionnaires can blur distinctions between load types (Greenberg & Zheng, 2023; Orru & Longo, 2019). Combining self-reports with objective indicators such as response time, eye-tracking, or physiological measures would strengthen validity. Third, findings derive from a single RME task focused on surface-area integration; cognitive patterns may differ for other mathematical topics such as differential equations or vector calculus. Future research should test the framework across multiple RME contexts to confirm its generalizability.

In summary, the results indicate that germane engagement plays a significant yet partial role in students' mental effort, mediated by contextual understanding and metacognitive regulation. The study contributes to theory by aligning CLT and RME within a practical instructional model that balances conceptual depth, task realism, and cognitive efficiency in engineering mathematics.

Conclusion

This study demonstrates that well-designed RME tasks in engineering mathematics can channel cognitive resources toward productive schema construction (germane load) while minimizing extraneous demands, even when intrinsic complexity is high. By integrating realistic contexts with guided reinvention and structured scaffolding, RME enables learners to engage deeply with conceptual understanding without cognitive overload. The proposed RME–CLT instructional framework provides a practical model for balancing realism, reflection, and efficiency in higher education mathematics.

Future research should extend this work through experimental comparisons between RME-based and traditional instruction to examine causal effects on learning efficiency; longitudinal tracking of cognitive load profiles across multiple mathematics courses to capture developmental patterns; and cross-disciplinary replications in fields such as mechanical or civil engineering to test the generalizability of the framework. Such studies would strengthen evidence for designing cognitively efficient, contextually meaningful instruction in STEM education.

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Conflicts of Interest

The authors declare no conflict of interest related to the design, implementation, or publication of this research.

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Author Contributions

Rindu Alriavindra Funny: Conceptualization, Methodology, Formal analysis, Investigation, Writing (original draft, Review & editing), Visualization, Project administration. **Fajar Khanif Rahmawati:** Resources, Data curation, Validation, Supervision, Funding acquisition.

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