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RESEARCH ARTICLE

DECODING COGNITIVE LOAD IN VIRTUAL CLASSROOMS: AN EMPIRICAL ANALYSIS OF CONCEPTUAL BARRIERS IN AC POWER FACTOR AMONG POLYTECHNIC STUDENTS

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Abstract

Emergency remote teaching during the post-pandemic transition shifted vocational laboratories online without adequate tactile infrastructure. This study investigated cognitive load and conceptual barriers among polytechnic Energy Engineering students (N=32) learning AC Power Factor in a fully virtual laboratory. Using a single-group pretest-posttest design, conceptual understanding was assessed across Revised Bloom's Taxonomy (C2–C4) together with a subjective cognitive load questionnaire. Descriptive analysis showed declines in C2 (-5%) and C3 (-3%), whereas C4 exhibited only a marginal 4% gain. Paired-sample t-tests indicated no significant improvement ($p>0.05$). Item-level triangulation identified severe overload in parallel calculations (C214, C409) and an illusion of competence in variable interactions (C416, C201). Proficiency profiling classified all students as overburde ned in C2, with performance polarization in C3 and virtual fatigue in C4.Standalone digital modules therefore failed as sufficient scaffolding, highlighting the need for synchronous instruction and adaptive visual simulations to reduce extraneous cognitive load.

Introduction:-

In the digital era, Online Learning (OL) for both theoretical and practical aspects have transformed into a mainstream instructional modality in engineering higher education. Although OL offers flexibility and accessibility, this full transition to virtual spaces presents significant cognitive challenges for students. In practical competency-based disciplines such as Energy Engineering, the absence of hands-on laboratory interaction is suspected to trigger higher cognitive load, which in turn can hinder the assimilation of complex conceptual knowledge (Zhang et al., 2025; Rathnayaka et al., 2024). According to Cognitive Load Theory (CLT), learning abstract engineering concepts in fully online environments imposes intrinsic cognitive load arising from the complexity of the subject matter and extraneous cognitive load associated with digital instructional environments, thereby taxing learners' limited working memory (Sweller, 2020; Yanto et al., 2026).

As an intrinsically complex concept, AC Power Factor (ACPF) is fundamental to the analysis and optimization of AC power systems because it requires integrating mathematical reasoning with vector-based and graphical

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representations (Ayers, 2024). Many students can apply power formulas procedurally but frequently fail to interpret the physical meaning of temporal phase shifts or phasor relationships between current and voltage under different load conditions, revealing persistent conceptual barriers.In fully online laboratory settings, the absence of hands-on interaction with laboratory equipment encourages students to rely on procedural formula memorization rather than developing robust physical intuition, thereby increasing the likelihood of conceptual barriers (Holton et al., 2008; Maries et al., 2022).

Several prior studies confirm that students' perception of difficulty toward electrical engineering material is heavily influenced by the limitations of digital visualization and the intensity of instructor assistance (Wahyudi et al., 2024). However, the current literature mostly still focuses on evaluating students' general satisfaction with e-learning or macro learning outcome performance (Hague, 2024; Martin & Bolliger, 2022; Muhibbin et al., 2022). Such macro-level evaluations cannot identify the specific conceptual domains in which students experience persistent learning difficulties. Consequently, little is known about how conceptual barriers emerge at the item and individual levels during fully online ACPF laboratory instruction. Item-level analysis enables educators to identify cognitive anomalies and persistent misconceptions that remain hidden in aggregate learning outcomes (Xie et al., 2021).This limitation is particularly evident in vocational polytechnic education, where such fine-grained evaluations remain scarce.

To fill this research gap, this study utilizes historical data from Quarter 2 (Q2) of 2022, a critical period officially governed by a series of institutional emergency regulations, such as the Director of Politeknik Negeri Bandung (POLBAN) Circular Letter Number 10 of 2022 (POLBAN, 2022a) and Number 08 of 2022 (POLBAN, 2022b). This strict restriction period represents a unique natural experiment condition, where the vocational education system was forced to adopt virtual spaces without mature tactile infrastructure readiness (Hodges et al., 2020; Crawford et al., 2020). This study aims to dissect the cognitive load of Politeknik Energy Engineering students through an empirical analysis of conceptual barriers in the ACPF material within an online laboratory ecosystem based on the policy mandate. The uniqueness of this research lies in the data triangulation method that maps students' conceptual accuracy through pre-tests and post-tests based on cognitive levels of the Revised Bloom's Taxonomy (granularly per question from 20 instruments and per individual from 32 respondents) as well as confirmed with a post-teaching-and-learning perception questionnaire. This combination of objective performance analysis and subjective perception data is highly crucial to evaluating the extent to which digital modules and instructional videos may help mitigate cognitive difficulties in vocational students, particularly in engineering laboratory learning where online resources must support students before and during complex laboratory tasks (Mayer, 2024; Rathnayaka et al., 2024).

Research Method:-

This study employed a quantitative single-group pretest–posttest natural experiment design (Precharattana et al., 2023). The design captured instructional practices implemented under Emergency Remote Teaching during the post-pandemic transition.In the absence of a control group, the study emphasizes item-level analysis and individual-level profiling rather than inter-group comparisons. However, because the present design does not include a control group, observed pre–post differences are interpreted as evidence of change rather than definitive causal evidence of instructional effectiveness (Knapp, 2016).

The participants of this research were one active class of students from the Energy Engineering Study Program at POLBAN, totaling 32 students (N=32). The class was selected because it was the only cohort enrolled in the compulsory ACPF laboratory course during the Emergency Remote Teaching period.All participants were assumed to have acquired prior knowledge of AC power factor concepts, either from their secondary education, the previous semester, or the theoretical, non-practical lectures during the semester the study was conducted.

The instructional intervention for the ACPF practicum was delivered through an integrated virtual learning environment that combined synchronous and asynchronous activities, reflecting the broader transition from conventional hands-on engineering laboratories to digitally mediated learning experiences (May et al., 2023).The virtual laboratory intervention consisted of five sequential stages: (1) Pre-test: Students completed a conceptual understanding test online before the intervention began; (2) Asynchronous Phase (Pre-Class): The lecturer uploaded the official laboratory module, two instructional videos, and laboratory data created by the lecturer to the POLBAN Learning Management System (LMS). The first video contained ACPF material covering both theoretical studies and experiments, while the second video demonstrated equipment introduction and real tool setups to produce three types of data: (a) series RL circuits (single coil) with source voltage variations, (b) series RLC circuits with source voltage variations, and (c) series RLC circuits with variations in resistance values (R) at a constant AC source voltage; (3) Synchronous Phase (Virtual Class): Participants were divided into eight small groups (each consisting of four students). Learning activities (material presentation and discussion) were conducted via Google Meet alternately according to a schedule based on the analysis of modules and instructional videos in the LMS; (4) Feedback & Responsi: After the virtual class, each group compiled a digital laboratory report and uploaded it to the LMS. The lecturer evaluated and provided direct written feedback within the system. Once all eight groups finished, the lecturer held a virtual responsi session to evaluate systemic common errors in student reports; and (5) Post-test & Questionnaire: At the end of the entire learning series, students retook the conceptual understanding test (post-test) and completed a cognitive load perception questionnaire online.

Research data were gathered using two main instruments designed and self-developed based on the target achievements of preliminary assignments and analytical questions within the POLBAN ACPF laboratory module: (1) Conceptual Understanding Test: Consists of 20 multiple-choice questions designed to measure students' higher-order thinking skills in applying and analyzing ACPF concepts. This test instrument was strictly developed and classified based on three cognitive levels of the Bloom's Taxonomy (Anderson & Krathwohl, 2001). The classification structure of this instrument includes: (a) Understanding Domain (C2): 7 questions (35%) to measure basic conceptual interpretation; (b) Applying Domain (C3): 5 questions (25%) to measure procedural-mathematical calculation execution; and (c) Analyzing Domain (C4): 8 questions (40%) to map the ability to integrate experimental data and spatial-geometric representations.This classification cross-references prior studies proving that the cognitive load may vary with the cognitive demands associated with different levels of Bloom's revised taxonomy, particularly when such tasks are performed in virtual learning environments (Sultanova, 2025a; Andersen & Makransky, 2021). These items specifically focus on students' ability to translate procedural-mathematical calculations into spatial-geometric representations, such as sinusoidal phase shifts and current-voltage phasor diagrams. (2) Cognitive Load Perception Questionnaire: This instrument is a subjective rating scale utilizing a 4-point Likert scale (1–4) without a midpoint. The questionnaire was administered to students immediately after the digital learning process concluded to measure the perceived task difficulty of each of the 20 items. Within the CLT framework, this item difficulty level represents a primary indicator of students' intrinsic cognitive load when interacting with material visualizations on digital screens (Schmeck et al., 2015)

Due to the emergency and physical interaction restrictions at the end of the pandemic period, this instrument was not developed through an external expert panel validation stage. However, evidence supporting the content validity of the assessment was obtained by systematically aligning each test item with the content structure, learning activities, and worksheet questions contained in the institution's official laboratory module (Biggs, 1996; Sundre & Thelk, 2010).To comprehensively dissect conceptual barriers and cognitive load, the data analysis in this study does not utilize aggregated class average scores. Instead, it employs a granular statistical triangulation technique that correlates three data variables: (1) Objective Item Performance: The distribution percentage of students correct and incorrect answers for each item (n = 20) between the pre-test and post-test sessions was examined to track specific cognitive anomalies (Walter & Smith, 2021; Smith et al., 2020). This performance analysis is classified based on Bloom's cognitive domain clusters (C2, C3, C4) to prove at which thinking level students experience the most acute conceptual barriers resulting from virtual class disruptions; (2) Subjective Difficulty Perception: The mean cognitive-load questionnaire score for each item was calculated to identify the ACPF concepts associated with the highest perceived mental effort when students translated mathematical formulas into visual-spatial phasor diagrams (Ouwehand et al., 2021); and (3) Individual Proficiency Profile: The distribution pattern of concept mastery for each individual student (N = 32) was examined to identify individual variations in conceptual understanding and changes in mastery following exposure to the digital module. This individual-level analysis complements the item-level analysis by revealing whether overall changes in performance were consistently distributed across students or concentrated among learner profiles.

Findings and Discussion:-

Bloom's Cognitive Domain Disruption

Descriptive statistics indicate contrasting cognitive anomalies across Bloom's thinking levels, although the continuity of these contrasts is statistically non-significant as shown in Table 1. In the C2 and C3 domains, students experienced acute conceptual barriers and showed a decline in post-digital module intervention; the C2 domain degraded to a greater extent than C3. In the C4 domain, an inverse phenomenon occurred where student performance increased from pre-test to post-test within a low category. Among these thinking domains, no pre-test mean was above 61 and no post-test mean was above 60. This proves that the disruption of virtual teaching and learning activities has degraded the thinking abilities in the C2 and C3 domains and has had a low impact on the C4 domain.

Table 1. Mean Measurement Results and Paired Sample t-Test of Cognitive Domains

N.	Cognitive domain	Pre-test	Post-test	N-Gain (%)	*df*	*p-Value*	Description
1	C2	40.2	37.1	-5	6	0.636	Non-significant
2	C3	60.6	59.4	-3	4	0.857	Non-significant
3	C4	43.0	45.3	4	7	0.846	Non-significant

The research results show a unique instructional phenomenon where the digital module intervention in OL did not produce a statistically significant change in cognitive performance across all tested Bloom's thinking levels (p-value > 0.05). Methodologically, the non-significance of this paired sample t-test is heavily influenced by the limitations of the relatively small sample size, as represented by the degrees of freedom (df) ranging between 4 and 7. In statistics, a small sample size limits the statistical power to detect intervention effects, so variations in scores between the pre-test and post-test tend to be considered random variations (by chance).Despite being statistically non-significant, descriptive analysis of the directional movement of the mean values reveals a contrasting pattern of cognitive degradation between thinking levels. In the C2 and C3 domains, a post-intervention score decline occurred by -5% and -3%, respectively. This negative trend in foundational skills indicates an accumulation of extraneous cognitive load due to the disrupted transition to the OL environment. The digital module used is suspected of being unable to optimally present simplifications of the abstract concepts of ACPF. Consequently, students experienced mental fatigue (mental overload) and a drop in attention when shifting from the pre-test to the post-test. This is in line with CLT (Sweller et al., 2011), as well as recent findings from Evans et al., (2024) and Al-Fahad et al., (2023), which demonstrate that OL without synchronous interaction frequently triggers mental fatigue in exact science materials. Less adaptive digital representations of complex topics risk triggering frustration and lowering students' short-term memory retention.

Conversely, a slight increase was found at the C4 level with an N-Gain of 4%. This increase in Higher-Order Thinking Skills (HOTS), despite being in the low category, indicates logical stimulation triggered by the challenge of analysis questions. However, considering that the mean post-test score for the C4 domain remained below the passing threshold (45.3), this increase is strongly suspected to be a floor effect or basic logical speculation by students when facing the evaluation instrument, rather than a representation of deep conceptual understanding.The fact that no post-test mean score exceeded 60 across all domains confirms that the one-way digital module has not been effective as independent digital scaffolding in OL. This finding provides a new direction: the effectiveness of digital scaffolding in complex exact science materials cannot stand alone; instead, it requires the integration of synchronous strategies based on active interaction (or adaptive feedback) amidst students' independent learning processes.

Mental Effort Hotspots in ACPF Concepts

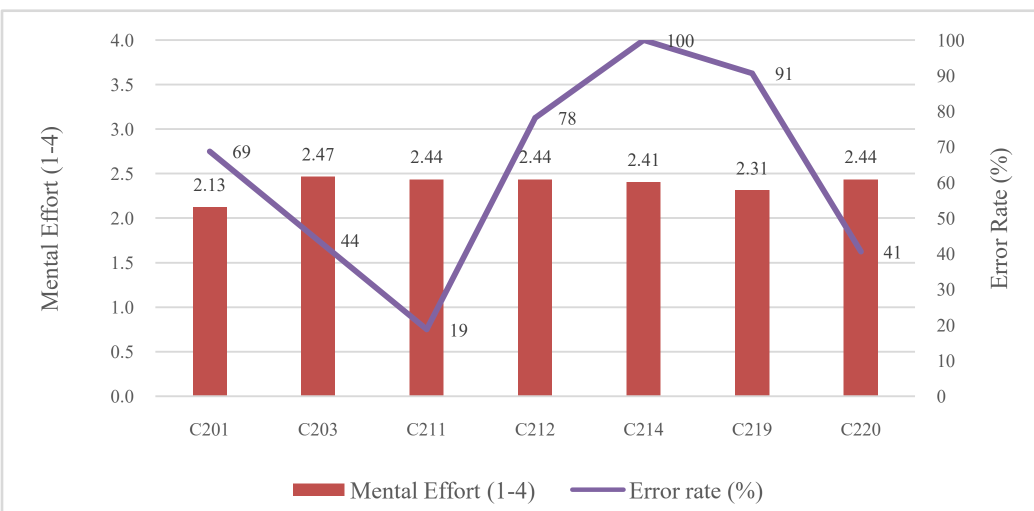

Figure 1a Students' ME and ER for each item in C2-domain

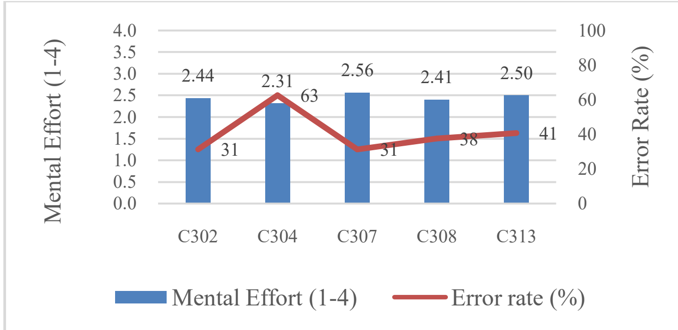

Figure 1b Students' ME and ER for each item in C3-domain

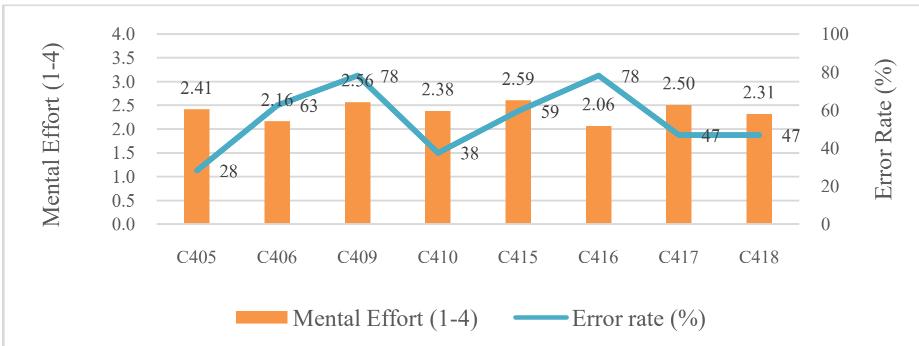

Figure 1c Students' ME and ER for each item in C4-domain

The empirical relationship between students' cognitive investment and their performance accuracy across various ACPF concepts is illustrated in Figure 1a, 1b, and 1c. The dual-axis visualization highlights critical fluctuations, demonstrating that higher mental effort (ME) does not always guarantee a lower error rate (ER). Instead, specific items exhibit distinct patterns of cognitive friction, which can be categorized into pedagogical 'hotspots' as visually detailed across the C2, C3, and C4 domains (Figure 1a, Figure 1b, and Figure 1c, respectively). This categorization is highly consistent with recent frameworks in digital learning architecture, where poorly optimized interface elements generate localized points of friction—often termed interaction hotspots—that misdirect students' cognitive resources from generative learning to interface decoding (Goceri, 2026; Xu et al., 2026).

To provide a deeper granular understanding of these cognitive phenomena, the question items were mapped into three distinct cognitive load quadrants based on the threshold interaction between ME and ER. This mapping is structured systematically in Table 2.

Table 2. Question Code Mapping Based on Cognitive Load Quadrants

N.	CLT Quadrant	Data Characteristics	Question Code	Core Competency	Cognitive Phenomenon Interpretation
1	I. Cognitive Overload	High ME (>2.40) High ER (>75%)	C214 C409	Understanding the causes of FD occurrence Predicting R, X_L, & $X_C$values for a specific FD	Extraneous load due to design flaws in digital instruments / locked answer keys. Intrinsic load is too high due to parallel mental computation overhead (manual trial-and-error).
2	II. Illusion of Competence	Low ME (<2.15) High ER (>65%)	C416 C201	Differentiating theoretical vs. experimental FD Understanding the variables that affect FD	Students rely on faulty intuition or thinking shortcuts (heuristics) without realizing there is a fundamental misconception.

3	III. High Cognitive Efficiency	High ME (>2.40) Low ER (<35%)	C211 C307	Understanding single-component FD (R/L/C). Calculating C during maximum FD (resonance).	Students' knowledge schema construction (germane load) is already mature, so a large investment of ME yields accurate results.

Note: The academic performance and cognitive load were mapped into a four-quadrant matrix (Mastery / Automaticity) based on the calculated thresholds. However, since no sub-concepts met the criteria for Quadrant IV (Low ME < 2.15 and Low ER < 35%), this quadrant was excluded from the empirical classification table.

As indicated in Table 2, items C214 and C409 triggered an extreme cognitive workload, characterized by high ME (>2.40) and high ER (> 75%). This specific trend in Quadrant I represents a severe state of Cognitive Overload and signifies pedagogical hotspots where cognitive demands exceed students' working memory capacity. From the perspective of Sweller's evolutionary cognitive architecture (Sweller et al., 2011), these items demand high biologically secondary knowledge, specifically complex parallel mathematical computations and the prediction of physical electrical variables (R, X_L, X_C). Because these tasks inherently possess high element interactivity, they strain the limited capacity of the human working memory, causing an overwhelming intrinsic cognitive load. According to van Merriënboer et al. (2024), when such highly complex tasks lack optimized procedural scaffolding, the compounding effect of high intrinsic and extraneous load inevitably causes cognitive breakdown, explaining why maximum ME still resulted in high ERs.

Furthermore, the data reveal that this overload is exacerbated by extraneous cognitive load. In digital learning environments, students may encounter formatting hurdles, rigid interface layouts, or other design features that require additional mental processing. Such poorly integrated instructional elements can induce a split-attention effect, forcing students to divide their attention between processing the instructional interface and solving the underlying engineering problem (Ayres & Sweller, 2021).This split-attention effect generates unnecessary mental friction, causing students to exhaust their cognitive resources on irrelevant processing rather than meaningful schema construction. To mitigate this extraneous load, future virtual instruction must implement scaffolding principles and split-attention reduction strategies, such as integrating mathematical formulas directly within the circuit simulation interface rather than forcing students to toggle between separate windows.

A contrasting phenomenon is observed in items C416 and C201, which fall into Quadrant II (Illusion of Competence). In these items, students reported low ME (<2.15) but generated exceptionally high ER (>65%). This gap implies that students subconsciously relied on flawed intuition or cognitive shortcuts (heuristics) without recognizing the fundamental conceptual gaps in their understanding. According to Sweller, Ayres and Kalyuga (2011), this state occurs when instructional materials fail to prompt adequate germane cognitive load, allowing superficial familiarity to mask deep-seated misconceptions. In this environment, students mistakenly believe they comprehend the distinction between theoretical and experimental data, leading to rapid, low-effort decisions that ultimately result in systemic errors. This discrepancy aligns with Mayer's (2024) concept of metacognitive miscalibration in digital platforms; when learning interfaces create a superficial sense of familiarity, students often bypass deep generative processing, leading to an inflation of confidence that manifests as high errors under low perceived cognitive load.

Conversely, items C211 and C307 exemplify High Cognitive Efficiency (Quadrant III), where high ME (>2.40) yielded successful outcomes with low ER (< 35%). This quadrant reflects an ideal instructional scenario where the student's heavy investment of ME is highly productive. This state occurs because the mental exertion is effectively funneled into germane cognitive load—the cognitive processing dedicated to constructing and automating cognitive schemata. This aligns with recent empirical findings by Zeitlhofer and Zumbach (2026), which demonstrate that complex tasks with 'desirable difficulties' promote effortful retrieval processes and deep cognitive engagement rather than performance failure. Since the foundational concepts of single-component systems (R/L/C) had already been matured and structured in the students' long-term memory, as conceptualized in productive ME frameworks (Firdaus et al., 2025), their working memory could effectively allocate its full capacity toward solving complex calculations, such as maximum resonance capacity, without experiencing cognitive breakdown.

While items in Quadrants I, II, and III highlight critical operational shifts, the remaining 14 items in Table 2 and Figure 1 exhibit stable distributions that confirm the baseline conceptual readiness of the students. Clusters of these remaining items are situated within the margins of Quadrant III, showing that while they demand considerable cognitive processing, the students' existing mental schemata for single-component systems successfully prevented cognitive breakdown.

Furthermore, the rest of the unaddressed items fall into the low workload sectors of Quadrant II and Quadrant IV. Items in Quadrant IV (Low ME, Low ER) serve as instructional baselines, representing fundamental tasks where automated cognitive schemata are already fully established in the students' long-term memory. Conversely, the remaining items clustered near the boundaries of Quadrant II do not meet the extreme threshold of pedagogical hotspots but still indicate mild analytical vulnerabilities where superficial familiarity prompts hasty, intuitive errors. By mapping all 20 items across the four quadrants, this comprehensive distribution demonstrates that cognitive friction is not uniform across the digital instrument; rather, it is highly localized within specific advanced tasks, while many of the items remain instructionally manageable (Table 2).

Proficiency Profiling and Digital Module Efficacy

An in-depth analysis regarding Intrinsic Cognitive Load and the improvement of learning outcomes (N-Gain) among polytechnic students is clustered based on Bloom's taxonomy, ranging from the C2, C3, to C4 domains. Through a proficiency profiling approach, the efficacy of the digital module used in the virtual classroom can be empirically evaluated, as described below.

1. Cognitive Domain C2: Foundational Crisis and Mental Overload

Based on the visualization in Figure 2, all students without exception fall into the Overburdened category. This group is characterized by a very high intrinsic cognitive load, falling within the score range of 2.0 to 3.0, which competes with random and even downward-trending negative N-Gain values.

This finding indicates a substantial foundational misconception among students. ACPF materials inherently involve abstract concepts such as active power, reactive power, apparent power, and phase relationships that require coordinated conceptual and mathematical representations. This is consistent with previous research documenting specific conceptual difficulties among engineering students in understanding the behavior of AC circuits, particularly those involving time-varying behavior and reactive components (Holton et al., 2008). The digital module currently used has been shown to have limitations in mitigating this complexity because it has not adequately simplified abstract concepts through interactive visualization. Such limitations may contribute to difficulties in constructing spatial representations and increase students' cognitive demands during the initial stages of learning (Sriadhi et al., 2022; Girmay et al., 2026). This foundational conceptual barrier at the C2 level may help explain why students' N-Gain scores are irregularly distributed and do not consistently demonstrate positive learning gains.

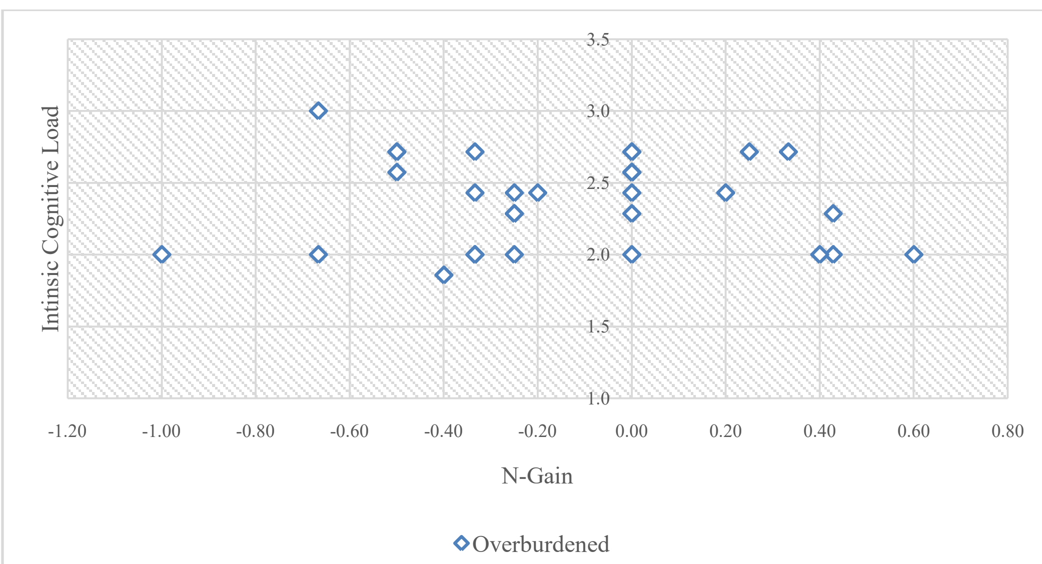

Figure 2. Distribution of N-Gain vs. Intrinsic Cognitive Load in the C2 Domain

2. Cognitive Domain C3: Ability Polarization and the Domino Effect

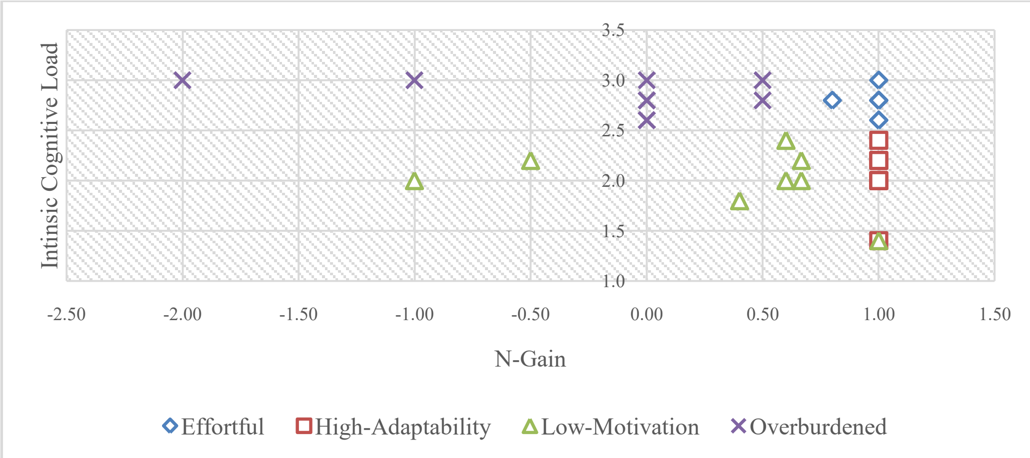

Figure 3. Distribution of N-Gain vs. Intrinsic Cognitive Load in the C3 Domain

Unlike the C2 domain, the data distribution in Figure 3 shows a polarization of student profiles into four distinct categories: Effortful, High-Adaptability, Low-Motivation, and Overburdened. This profile differentiation begins to emerge when the learning process enters the stage of calculating power factor formulas. At this calculation stage, differences in students' initial mathematical abilities may act as a key separating factor. Differences in prior knowledge can affect how learners process new information and respond to instructional support, while insufficient topic-specific mathematical knowledge may also influence subsequent learning outcomes (Alreshidi, 2023; Kalyuga, 2007). Students with strong mathematical logic skills can adapt quickly, thus entering the High-Adaptability profile with high N-Gain achievements (reaching a score of 1.00).

Conversely, students who have already experienced conceptual comprehension failure at the basic C2 level may face a destructive “domino effect.” Unresolved gaps in conceptual understanding can increase the cognitive demands of subsequent problem-solving tasks because students have fewer well-developed schemas available to support the processing of complex information (Sweller, 1988). Based on the graph visualization, this domino effect triggers the appearance of the Effortful profile (blue diamond) and Low-Motivation profile (green triangle) trapped in an extreme negative N-Gain zone ranging from -2.50 to -0.50. Meanwhile, the Overburdened profile (blue cross) heavily clusters around the near-zero N-Gain area with maximum Intrinsic Cognitive Load levels (scores of 2.5 to 3.0), indicating that their working memory capacity is completely exhausted just to process calculation procedures without producing any improvement in understanding.

3. Cognitive Domain C4: HOTS Demands and Virtual Fatigue

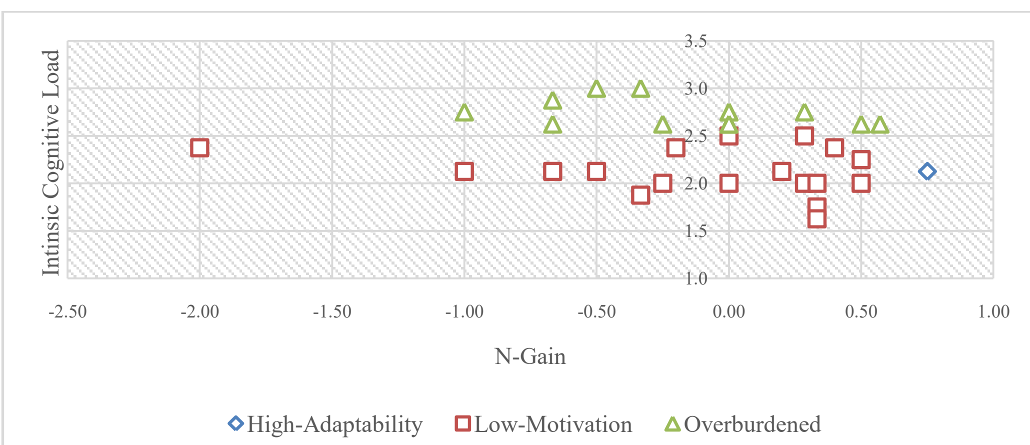

Figure 4. Distribution of N-Gain vs. Intrinsic Cognitive Load in the C4 Domain

In the analysis domain graph shown in Figure 4, a worrying trend shift occurs where the data distribution is dominated by the Low-Motivation profile (orange square) and the Overburdened profile (green triangle). This phenomenon may reflect difficulties in engaging with higher-order cognitive tasks, such as conducting power factor correction analysis and determining optimal capacitor values. Such difficulties may be influenced by differences in students’ prior mathematical knowledge and expertise, which can affect their processing of new and complex information (Alreshidi, 2023; Kalyuga, 2007).

The high complexity of analysis tasks in virtual classroom environments triggers acute academic frustration. Drawing on Sultanova’s (2025b) conceptualization of non-cognitive load, excessive cognitive, emotional, and motivational demands in OL may contribute to students’ emotional strain and fatigue, potentially undermining their motivational engagement. Consequently, the student group with a Low-Motivation profile clusters massively in the negative N-Gain area (ranging from -2.00 to -0.50) as a form of self-defense against academic frustration.

On the other hand, students with an Overburdened profile dominate the low-to-moderate positive N-Gain area (0.00 to 0.50), but they must allocate an extraordinary amount of cognitive effort. This is evident from their position at the highest Intrinsic Cognitive Load coordinates, spanning a score range of 2.50 to 3.50. This failure to translate ME into optimal learning outcomes may be exacerbated by the absence of adaptive scaffolding functions within the digital module. Such scaffolding may help learners manage the complexity of technical analytical tasks while reducing unnecessary cognitive demands and preserving limited cognitive resources for learning (Sweller et al., 2011; Sweller, 2020).

4. Digital Module Efficacy: Scaffolding Failure from a Cognitive Load Perspective

Comprehensively, the findings of this research suggest that the digital module currently applied may be ineffective in facilitating independent learning of ACPF materials in virtual classrooms. This may occur when technical information is transferred to a digital environment without sufficient consideration of learners' limited working-memory capacity or the reduction of unnecessary cognitive processing. From the perspectives of CLT and the Cognitive Theory of Multimedia Learning, instructional materials should be structured to manage cognitive demands and facilitate the effective integration of verbal and visual representations (Sweller, 2020; Mayer, 2024).

Data processing results prove the existence of a structured cognitive crisis where the module fails to facilitate personalized learning pathways, despite student proficiency profiles proving to be fragmented since the C3 domain. This lack of adaptivity is validated by Rahmawati et al. (2026) as the primary cause of collapsing digital learning media efficacy in engineering education. Furthermore, the massive appearance of negative N-Gain values in the C2, C3, and C4 domains serves as a valid alarm that this digital module confuses students rather than providing academic clarity. This phenomenon can be interpreted through the Expertise Reversal Effect described by Kalyuga (2007), whereby instructional guidance that supports learners with limited prior knowledge may become redundant or counterproductive for more knowledgeable learners. In technology-mediated learning, therefore, instructional support needs to be appropriately calibrated to learners’ prior knowledge and cognitive demands (Kalyuga, 2007; Sweller, 2020).

Based on the CLT developed by Sweller (1988), this uninteractive presentation format is proven to aggravate extraneous cognitive load. As a result, students' mental capacity is completely drained processing poor module design, thereby inhibiting the emergence of germane cognitive load necessary for building a deep conceptual understanding of ACPF.

Granular Triangulation: Unveiling the Hidden Conceptual Barriers

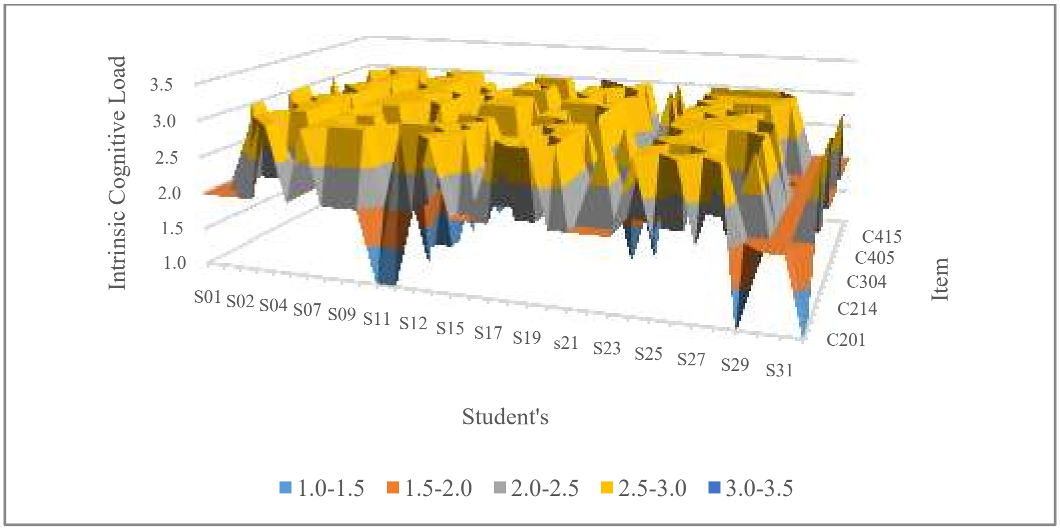

Figure 5. 3-D Topographical Mapping of Perceived Intrinsic Cognitive Load Across Bloom's Taxonomy Levels

Through granular statistical triangulation, a 'Hidden Conceptual Barrier' phenomenon was discovered, as shown in Figure 5. The graph is visually dominated by Yellow (Range 2.5 – 3.0), which forms a broad plateau at the top. This confirms that the mental workload (ME) of most students sits at the highest critical level found in the field, touching an average score of 3.0. Although this research instrument utilizes a Likert scale of 1–4 without a midpoint, no single question item reached an absolute score of 4; therefore, the upper limit of the graph visualization is strictly cut off at 3.5 to focus data contrast. Underneath the yellow layer, there is a consistent Grey supporting wall (Range 2.0 - 2.5), reinforcing that cognitive load never systematically levels off to a low level (Scale 1.0), even for students with high N-Gain rankings (S25 - S32). This visualization change proves the effectiveness of the Granular Triangulation method used. By strictly limiting the upper boundary of the graph to a scale of 3.5, the contrast between the yellow plateau (high load) and the tip of the blue cone (low load) is highly evident. This pattern confirms that the cognitive instrument successfully captured micro-level fluctuations of intrinsic cognitive load (per question item), rather than mere macro averages that often cause bias.

The most interesting finding in this figure is the appearance of a sharp, inverted cone valley (Cognitive Stalactite) piercing downward to touch the Orange (1.5 – 2.0) and Blue (1.0 - 1.5) color zones. These valleys act as "positive anomalies" and only occur sporadically at specific coordinate points, namely in the Middle Student Zone (detected at coordinate S11 in the C201 - C219 question area) and the High Student Zone (detected very sharply at coordinates S29 and S31 specifically in the foundational C201 question area).

Theoretically, the phenomenon in Figure 5 indicates a cognitive transition fracture. The applied OL is proven only capable of facilitating static definitional comprehension (e.g., memorizing power factor formulas). As soon as question indicators shift slightly toward relationships between variables (e.g., the impact of inductive load on phase angle displacement θ), element interactivity increases sharply. Consequently, students' working memory capacity instantly experiences overload (jumping from the blue color straight to yellow). This spike in intrinsic load due to abstract content complexity is in line with cognitive load management analyses, which have proven that shifting from memorization toward relational understanding between variables triggers extreme mental workload spikes if not mitigated by adaptive instructional design (Hindriana et al., 2026). This explains why the majority of students' N-Gains cluster in the low category.

The sharp cone on student S11 in the C201 domain is a unique novelty finding. Student S11 is in the lower-middle N-Gain profile group yet possessed a very low cognitive load on that specific question. In the perspective of CLT, this is categorized as an isolated success due to external factors in the virtual classroom (e.g., the student accidentally gained insight from a video simulation snippet or independent explanation on the internet). This external multimedia assistance acted as visual scaffolding that suppressed extraneous load. Nonetheless, digital ecosystem studies by Wang and San Diego (2025) warn that unstructured multimodal stimuli over a sustained period only produce temporary cognitive relief. As a result, the understanding formed tends to be superficial and fails to transfer to subsequent questions.

Conclusions:-

This study examined the cognitive load dynamics and conceptual barriers experienced by polytechnic Energy Engineering students during a fully online AC Power Factor (ACPF) practical course under emergency remote teaching conditions. The findings demonstrate that standalone one-way digital instructional modules provide insufficient scaffolding for learning highly abstract engineering concepts. Descriptive analyses revealed cognitive deterioration in the foundational C2 and C3 domains, with post-intervention scores declining by 5% and 3%, respectively, whereas the modest 4% improvement observed in C4 most likely reflected a floor effect rather than genuine conceptual mastery. Consistently, paired sample t-tests indicated no statistically significant learning gains. Granular item-level triangulation further identified two critical pedagogical barriers: severe cognitive overload during complex parallel computations (C214 and C409) and an illusion of competence in theoretical reasoning (C416 and C201), where incorrect intuition concealed persistent misconceptions. Student proficiency profiling additionally revealed a systemic weakness in foundational understanding, classifying all participants as Overburdened in C2, accompanied by marked performance polarization in C3 and widespread virtual fatigue under higher-order analytical tasks in C4. Collectively, these findings indicate a cognitive transition fracture between procedural formula application and relational conceptual reasoning, helping explain why one-way digital instruction may intensify extraneous cognitive load among novice engineering learners. Therefore, future digital engineering curricula should integrate adaptive scaffolding, interactive visual simulations, and synchronous feedback mechanisms to reduce extraneous cognitive load and promote meaningful schema construction.

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Author Contributions:-

The sole author (IG.R.) was responsible for conceptualization, methodology, validation, investigation, data curation, formal analysis, visualization, writing—original draft preparation, and writing—review and editing. The author has read and agreed to the published version of the manuscript.

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The authors declare no conflict of interest.

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