Improving Online Learning Outcomes through Media Diversity: An Experimental Study on Its Moderating Role in Learner Extraneous Cognitive Load and Performance

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***Abstract*—In online learning environments, the use of diverse media formats to deliver instruction is widespread, yet their effect on learners' cognitive load and performance remains contested. Guided by Cognitive Load Theory, this study examined whether media diversity moderates the effects of Extraneous Cognitive Load (ECL) on learner performance during online learning. An experimental design was implemented in Moodle with 362 undergraduate students enrolled in an online computing course at a public university in East Africa. Learners were randomly assigned to a treatment group exposed to media-rich content or a control group using text-only materials. Data were collected from Moodle log files and self-report questionnaires. Data analysis was conducted in Python using mixed-effects linear regression models. Results showed that engagement (course views)-ECL proxy was a strong predictor of learning outcomes. Higher engagement (course views) was positively associated with behavioral performance (course activity completions; $\beta = 0.518$, $p = 0.001$) and cognitive performance (quiz scores; $\beta = 0.409$, $p < 0.001$). A significant negative interaction between engagement (course views) and media diversity was observed for both behavioral performance ($\beta = -0.239$, $p < 0.001$) and cognitive performance ($\beta = -0.195$, $p < 0.001$). Simple slopes analysis showed the positive effect of engagement (course views) weakened as media diversity increased (behavioral performance: $\beta = 0.619$ to $\beta = 0.416$; cognitive performance: $\beta = 0.491$ to $\beta = 0.326$). These findings show that increased media diversity elevates extraneous cognitive load, thereby reducing learners' performance and underscore the need for cognitively aware media design in online learning environments.**

***Keywords*—cognitive load theory, extraneous load, learning analytics, media diversity, Moodle, online learning, performance**

I. Introduction

The rapid growth of digital technologies has significantly reshaped higher education, with online learning environments becoming an integral part of instructional delivery worldwide [1]. Platforms such as Moodle, Blackboard, and Canvas have expanded opportunities for flexible and scalable learning, especially in contexts where access to traditional classrooms is limited [2]. Within these digital platforms, instructional design choices are central to how learners engage with course content and construct knowledge [3]. One emerging design feature is media diversity, the integration of diverse media formats such as text, audio, and video within online learning interfaces to enrich learning experiences. Advocates argue that media-rich learning environments promote engagement and deeper understanding by stimulating multiple cognitive channels [4]. However, empirical evidence on their impact on learning experiences is mixed, as some researchers argue that the use of diverse media may overwhelm learners, leading to cognitive overload and reduced learning efficiency [5]. However, Cognitive Load Theory (CLT) provides a useful theoretical lens for understanding these challenges [6].

CLT posits that human working memory has a limited capacity [7]. It further asserts that learning outcomes are determined by how instructional design affects this limited capacity of working memory [8]. Therefore, during the design of online learning systems, it is crucial to account for the limited capacity of learners' working memory [9]. Partarakis *et al.* [10] emphasize that CLT is a fundamental framework for designing effective online learning interfaces. Within this framework, cognitive load comprises three components: intrinsic, extraneous, and germane. Intrinsic load reflects the inherent complexity of the learning task and the level of prior knowledge required to process it [11]. Germane load involves the mental effort devoted to constructing and automating schemas, which directly supports learning [12]. In contrast, extraneous cognitive load arises from poorly designed instructional materials or interface features that consume working memory without contributing to learning [13]. While intrinsic load is largely determined by task complexity, and germane load can be optimized through effective scaffolding, extraneous load is the most amenable to instructional design interventions [14]. Kalyuga [15] refers to extraneous cognitive load as "bad load" as it diverts cognitive resources to irrelevant learning, while referring to germane load as "good load" since it is associated with essential element processing and schema creation. CLT emphasizes that instructional design should aim to minimize learners' extraneous cognitive load to optimize working memory resources for maximum learning outcomes.

In online learning environments, where media elements, navigation structures, and information presentation vary widely, high extraneous load can easily overwhelm learners' cognitive resources, leading to disorientation, reduced germane processing, and lower performance outcomes [16]. Therefore, strategically managing and reducing extraneous cognitive load becomes essential to free up cognitive capacity for deeper processing and schema construction, making it a critical focal point for improving online learning effectiveness. Longo *et al.* [17] argue that to support meaningful learning, online instructional environments must be designed to manage learners' extraneous cognitive load.

Choi *et al.* [18] aver that by reducing extraneous cognitive load, which interferes with the learning process, optimal performance can be achieved. According to Mayer *et al.* [16], media diversity may reduce extraneous cognitive load by presenting information to learners in complementary formats across visual and auditory channels, thereby improving performance. Huang *et al.* [19] argue that media diversity is a frequently applied principle in online learning design. Some studies, such as Costley *et al.* [20], contend that media diversity may lead to increased cognitive load and, consequently, lower performance.

Although extensive research has explored the general effects of multimedia learning, limited empirical evidence exists on whether and how media diversity moderates the relationship between extraneous cognitive load and learner performance during online learning. Most prior studies have examined media types in isolation or compared multimedia against traditional text-based approaches [21]. Few have explicitly investigated whether media diversity can buffer the negative effects of extraneous cognitive load on learner performance in authentic online learning settings.

This gap is particularly relevant in higher education contexts, where learners must often navigate multiple resources and media formats simultaneously [22]. Therefore, without clear empirical evidence, educators risk underutilizing or misapplying diverse media in ways that may inadvertently increase learners' extraneous cognitive load. For instance, in Sub-Saharan Africa, resource-constrained settings, where online learning adoption has accelerated in many public universities but instructional design practices remain uneven, such evidence is crucial [23]. Especially during and post-COVID-19 pandemic. To support student success in these settings, effective integration of diverse media could enhance learning outcomes by mitigating extraneous cognitive load [24].

The present study applies Cognitive Load Theory to investigate how media diversity moderates the relationship between extraneous cognitive load and learner performance during online learning. While prior research has established the effects of cognitive load on learning outcomes, few studies have empirically tested how varying media modalities can either amplify or mitigate extraneous load in authentic online learning contexts. Accordingly, the research question guiding this study is: Does media diversity moderate the relationship between extraneous cognitive load and learner performance in online learning environments? To answer this research question, an experimental design was implemented using Moodle with undergraduate computing students at a public university in East Africa. A treatment group engaged with media-rich instructional content, whereas a control group accessed text-only resources. The findings contribute empirical evidence to clarify the role of media diversity in online learning, offering theoretical insights for CLT and practical guidance for designing cognitively aware, media-balanced digital learning environments.

II. Literature Review

Building on the background of the existing problem and the gap in research, and the theoretical foundation outlined in the introduction section, this section reviews relevant scholarship on media diversity, cognitive load, and learner performance in online learning environments. The review is organized in three strands: (a) Cognitive Load Theory in online learning, (b) cognitive load, media diversity, and performance in online learning, and (c) learning analytics in the Moodle learning management system. By synthesizing insights from these strands, the review establishes the conceptual and empirical basis for examining media diversity as a moderator of the relationship between extraneous cognitive load and learner performance in online learning environments.

A. Cognitive Load Theory in Online Learning

Online learning environments are digital platforms that use the internet and various digital tools to facilitate teaching and learning without physical presence [25]. As the demand for technological innovations in higher education rises, the design of these online learning interfaces has become critical in shaping cognitive processing and performance of learners [3]. Based on Cognitive Load Theory (CLT), which views that learners' working memory has a limitation of absorption during the learning process [9], presenting online instructional materials should be keenly considered. Therefore, CLT provides a framework to analyze how learners process the presented learning materials. This framework provides an understanding of the cognitive architecture of humans through the optics of intrinsic, extraneous, and germane loads [15]. For instance, when the learning tasks are difficult for learners, intrinsic cognitive load is imposed [13]. If the learning materials are presented in a way that learners cannot connect the elements between them, extraneous load is imposed on learners [26]. Other scholars refer to extraneous load as "bad load". It results from poor instructional design that diverts attention away from learning.

In the context of online learning, extraneous cognitive load is of key interest to researchers, as learners often face fragmented resources, non-linear navigation, and varying levels of multimedia integration [27]. Germane load is "a good one" since it's used for schema construction during learning [28]. Therefore, to support meaningful learning, extraneous load must be minimized [17]. This is because reducing extraneous load creates space for germane load, thus improving performance [18]. Empirical research in cognitive load theory consistently demonstrates that the structure and design of online learning environments significantly shape learners' cognitive experiences and outcomes.

Building on this, Hirtz and Harper [29] emphasized the importance of clear instructional organization in digital environments, showing that poorly structured content can increase cognitive load and lower satisfaction. Noroozi *et al.* [30] demonstrated that structured online discussions can compensate for suboptimal information presentation by offering cognitive scaffolds that enhance knowledge construction. Collectively, these studies underscore that online learning should offer environments that don't disadvantage learners cognitively, since this affects their performance.

B. Cognitive Load, Media Diversity, and Performance in Online Learning

Media diversity in online learning refers to the use of

various multimedia formats (videos, audio, text, and images) to present learning content and instruction to learners [31]. Online learning environments are witnessing more usage of diverse media during content presentation [19]. Diverse media engage multiple sensory channels, which helps to prevent overload on a single channel [10]. These are views of the "modality effects" principle [32]. According to Mayer's [33] multimedia learning principles, this application should be adopted in online learning pedagogy. An idea supported by Mayer *et al.* [16] dual coding principle, stating that the combined use of auditory and visual channels can reduce extraneous cognitive load and improve comprehension.

Existing empirical evidence suggests that when aligned with cognitive load theory guidelines, media diversity can enhance comprehension, promote deeper engagement, and accommodate diverse learning preferences [34]. Studies have shown that combining visual and auditory modalities can facilitate dual-channel processing, reducing the likelihood of overload on any single channel [35]. However, contrary findings exist.

Weng *et al.* [36] and Chuang *et al.* [37] argue that media diversity can impose additional cognitive demands, sometimes hindering performance. Some research cautions that excessive or irrelevant media elements may increase extraneous load and distract from core learning goals [38]. This inconsistency reveals a tension that media diversity may reduce or exacerbate extraneous cognitive load depending on design quality [39]. This tension highlights the importance of intentional and theory-driven use of media diversity in online learning environments.

Despite the growing body of research, much of the literature has treated cognitive load and multimedia effects separately, overlooking their interaction [39, 40]. Some studies have explored the direct effects of multimedia use on performance, such as the studies of Robertson *et al.* [41] and Juhanie *et al.* [42], but few have examined whether media diversity moderates the relationship between extraneous cognitive load and learner performance. In real-world systems such as Moodle, this represents a significant gap. The present study addresses this by investigating whether media diversity conditions the effect of extraneous cognitive load on learner performance in Moodle-based online learning environments. In doing so, it contributes both theoretical refinement to CLT and instructional design practices in online learning contexts in higher education.

C. Measuring Extraneous Cognitive Load and Performance in Online Learning

To understand how cognitive load influences learner performance in online learning, it is important to understand how it is measured [41]. According to the research by Juhanie *et al.* [42] and Rajabalee *et al.* [43], making accurate measurements for each cognitive load type (extraneous, intrinsic, and germane load) is critical for both research and instructional design.

The literature provides various techniques for measuring cognitive load. A subjective approach is used to assess learners' cognitive load through self-report questionnaires [44, 45]. Following the approach of Klepsch [46]extraneous load is measured subjectively using a multi-item self-report instrument administered immediately after each learning activity. Learners rate their perceptions of instructional clarity, relevance of information, and task presentation on a 10-point Likert scale ranging from 1 (strongly disagree) to 10 (strongly agree). Sample items include statements such as "The instructions and/or explanations during the activity were unclear" and "The learning materials contained information that was confusing or not directly relevant to the task". The mean score of these items represents the extraneous cognitive load level for each learner. Higher scores indicate increased cognitive burden due to inefficient instructional design, while lower scores reflect more streamlined and cognitively supportive learning environments.

Objective techniques involve the use of physiological measures such as eye-tracking and pupil dilation, which provide real-time insights into learners' cognitive load. However, these methods are not often feasible for large-scale online learning environments due to their complexity and resource demands [47, 48]. In response to these limitations, data analytics techniques have become increasingly relevant in digital learning contexts. These approaches leverage learners' behavioral log data captured in the Learning Management Systems (LMS) such as Moodle. By analyzing metrics that reflect engagement and cognitive activity, researchers can infer learners' cognitive load states without relying on intrusive measurement tools [1, 49].

D. Learning Analytics in Moodle Learning Management System

Learning analytics has emerged as a critical approach for understanding and improving online learning processes through the systematic analysis of data generated within Learning Management Systems (LMS). Moodle generates massive, unobtrusive, and scalable learner behavioral data, which offers a rich empirical foundation for examining how learners interact with instructional materials and for providing indicators for diagnosing potential cognitive challenges [50]. Increasingly, researchers are leveraging Moodle log data to uncover patterns of learner engagement and behavioral interaction [51, 52].

Cognitive Load Theory provides a powerful theoretical framework for deepening the interpretation of such behavioral traces by linking them to underlying cognitive processes [53]. In particular, indicators such as course views, module views, quiz attempts, and forum participation can be operationalized as proxies for different forms of cognitive load, especially extraneous cognitive load [1, 50].

A central conceptual framework for this mapping is the Moodle cognitive depth indicator model, which conceptualizes cognitive depth as "the extent to which learners in an online learning community construct meaning through sustained interaction and engagement with content" [53, 54]. This model classifies learner activity into a hierarchical sequence of levels, reflecting increasing depth of cognitive engagement. It begins with Level 0-Activity not viewed, indicating no engagement and purely passive exposure, and progresses through Level 1-Activity viewed (surface engagement), and Level 2-Content submitted to the activity (task interaction), up to Level 5, which reflects the highest level of active contribution and integration feedback.

These hierarchical levels provide a structured way to interpret how learners interact with and process online learning materials, thereby serving as a useful lens for linking observable behavior to underlying cognitive processes.

These levels can be systematically aligned with cognitive load theory views. Conceptually, lower levels of cognitive depth (e.g., Level 0) often correspond to high extraneous cognitive load, reflecting learner disorientation, fragmented navigation, or superficial engagement. In contrast, higher levels (e.g., Level 1 and above) are associated with lower extraneous load and a greater allocation of cognitive resources to germane load, which supports schema construction and meaningful learning [51, 55, 56]. For example, frequent course or module views accompanied by timely task completions may indicate minimal extraneous cognitive barriers and stronger engagement (Level 1). Conversely, high viewing frequencies without corresponding task completions may signal extraneous cognitive overload or interface-induced disorientation (Level 0). According to Krishnan *et al.*'s study [51], learners who passively navigate courses/modules tend to have signs of cognitive burden emanating from the learning interface rather than meaningful learning engagement.

On the other hand, learner performance is typically assessed through outcome-based measures such as test scores, task completions, and grades, complemented by LMS-specific indicators including course activity completion rates and quiz performance [50]. When examined together, cognitive depth indicators and performance outcomes offer a robust analytical framework for investigating how learning instructional design and interface architecture influence cognitive load and learning achievement in Moodle environments.

E. Conceptual Framework and Hypotheses Formulation

The reviewed literature highlights critical insights on how instructional design features influence learning outcomes. Grounded in Cognitive Load Theory [9], this study examines the relationship among Extraneous Cognitive Load (ECL), Media Diversity (MD), and learner performance in online learning environments. CLT posits that extraneous load, caused by poorly designed instructional materials, consumes cognitive resources without contributing to schema construction, thereby hindering performance. Although diverse media, such as text, images, audio, and video, can engage multiple cognitive channels to support learning [16, 57], empirical evidence on their impact on learning outcomes in online environments remains limited [31].

Building on these insights, this study hypothesizes that ECL negatively affects learner performance and that media diversity moderates the relationship between ECL and performance in online learning environments.

To empirically test these assumptions, a mixed-effects repeated measures modeling approach was employed. This approach accounts for repeated observations from the same learners (each participant measured at two points: Week 1 baseline and Week 2 post-intervention), which introduces statistical dependence between measurements from the same individual. The general form of the mixed-effects model was specified as:

$$\text{Performance}_{it} = \beta_0 + \beta_1 \text{Time}_t + \beta_2 \text{E}_{it} + \beta_3 \text{MD}_i + \beta_4 (\text{E}_{it} \times \text{MD}_i) + \beta_5 (\text{Time}_t \times \text{MD}_i) + U_i + \epsilon_{it}$$

where:

- Performance is the dependent variable, operationalized using course activity completions (behavioral performance) and quiz scores (cognitive performance).
- i indexes learners and t indexes time (0 = week 1baseline, 1 = week 2 post-intervention),
- β_0 is the grand intercept, representing average baseline performance for control-group learners with mean engagement,
- β_1 (Time effect) captures the overall change in performance from baseline to post-intervention,
- β_2 (ECL main effect) represents the effect of engagement (course views), used as a behavioral indicator of extraneous cognitive load on performance,
- β_3 (MD main effect) captures between-group differences between learners exposed to media-rich instructional materials (treatment) and text-only materials (control),
- β_4 (E × MD interaction) tests whether media diversity moderates the relationship between extraneous cognitive load and performance,
- β_5 (Time × MD interaction) assesses whether exposure to media-rich materials alters the rate of performance change over time,
- U_i is a random intercept capturing stable, learner-specific differences not explained by the fixed effects.
- ϵ_{it} is the within-learner residual error term.

Time was coded as 0 = Week 1(baseline) and 1 = Week 2 (post-intervention). Media Diversity (MD) was treated as a between-subject variable (0 = control, 1 = treatment). Engagement (E), measured via course views, was mean-centered before analysis to facilitate interpretation of interaction effects. Fig. 1 illustrates the conceptual framework, showing both the direct effect of ECL on performance and the moderating role of media diversity.

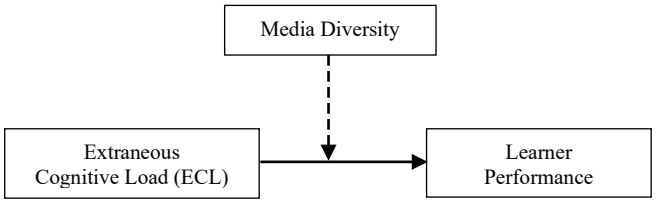

Fig. 1. Conceptual framework of media diversity moderating the link between extraneous cognitive load and learner performance.

Since performance in online learning manifests in both behavioral and cognitive forms, two parallel mixed-effects models were estimated using the same fixed and random-effects structure but different dependent variables. This two-model approach allowed examination of whether extraneous cognitive load and media diversity exhibit consistent or differential effects across performance dimensions, serving as an internal robustness check of the proposed moderation framework.

1) Model 1(behavioral performance)

The first model operationalized performance as behavioral performance, measured using course activity completion counts, which reflect learners' ability to successfully execute required learning tasks within the LMS [58–60]. The model

was specified as:

$$Bperf_{it} = \beta_0 + \beta_1 Time_t + \beta_2 Engagement_{it} + \beta_3 MD_i + \beta_4 (Engagement_{it} \times MD_i) + \beta_5 (Time_t \times MD_i) + u_i$$

This model examines whether:

(1) Engagement (course views), as a proxy for extraneous cognitive load, predicts observable task completion.
(2) Media diversity influences behavioral performance.
(3) Media diversity moderates the relationship between engagement (course views) and behavioral performance.

2) Model 2 (cognitive performance)-sensitivity analysis

To assess the robustness of the proposed moderation model, a second mixed-effects model was estimated using cognitive performance, operationalized as quiz/exam scores, as the dependent variable [61]. The model was specified as:

$$Cperf_{it} = \beta_0 + \beta_1 Time_t + \beta_2 Engagement_{it} + \beta_3 MD_i + \beta_4 (Engagement_{it} \times MD_i) + \beta_5 (Time_t \times MDi) + u_i$$

The fixed-effects structure mirrors model 1, and learners are again modeled as random intercepts. This sensitivity analysis evaluates whether the extraneous cognitive load and the moderating role of media diversity persist for learning outcomes requiring knowledge acquisition, rather than execution alone.

3) Hypotheses

Based on the conceptual framework, the following three null hypotheses were formulated:

H01: There is no significant relationship between extraneous cognitive load and learner performance in online learning environments.

H02: There is no significant relationship between media diversity and learner performance in online learning environments.

H03: Media diversity does not significantly moderate the relationship between extraneous cognitive load and learner performance in online learning environments.

III. Materials and Methods

This section outlines the methodological procedures adopted to test the formulated hypotheses to examine the relationship between extraneous cognitive load, media diversity, and learner performance in an online learning environment.

A. Research Design

An experimental research design was employed to test the formulated hypotheses. The study population comprised 842 undergraduate students enrolled in six computing-related programs at a public university in East Africa during the semester of study. To provide a uniform learning context, a short course on the Laravel framework, a widely used web development tool, was developed and delivered through a Moodle-based online learning interface. This approach ensured consistent content delivery and generated sufficient system log data for subsequent analysis.

From the same learning content, two versions of instructional materials were developed while maintaining the scope of content and learning objectives. Version 1 presented the content in text-only format, whereas Version 2 incorporated audio, video, and text. Both versions were prepared by the same subject matter expert to ensure content validity, and learning sessions were scheduled for equal duration across groups.

During week 1, both the treatment and control groups engaged with Version 1 content to establish baseline measures for comparison [62]. In week 2, the control group continued with Version 1 content, while the treatment group received Version 2 content. To ensure that no participant was academically disadvantaged, all learners were subsequently exposed to the version of the content they had not received during the experiment.

B. Sample Selection and Participants

The sample was determined using Cochran's formula, based on a 95% confidence level, 5% margin of error, and a $p = 0.5$, resulting in a sample size of 385. Stratified sampling was then applied to ensure proportional representation across the six academic programs, yielding 362 students who consented to participate in the study, representing 94.03% of the calculated sample. Although this was slightly fewer than the calculated sample size (by 5.97%), it exceeded the minimum requirement of 15 participants per group for valid experimental analysis [63]. Participants were randomly assigned to either the treatment group or control group using Excel's RAND() function [64], which minimized allocation bias and ensured balanced representation across the academic programs [65].

C. Data Collection and Analysis

Data were collected from two complementary sources: Moodle system logs and self-reported cognitive load questionnaires, enabling both behavioral and subjective assessment of learners' cognitive experiences.

1) Moodle log data (behavioral measures)

Learning analytics data for both treatment and control groups were extracted from the Moodle logging system across two time points: week one (pre-intervention) and week two (post-intervention). This longitudinal structure enabled comparison of learner behavior before and after the introduction of media diversity. The logs provided objective indicators of learner learning behavior.

Course views were operationalized as a behavioral proxy for Extraneous Cognitive Load (ECL). Consistent with previous learning analytics research, higher learning engagement (course views) was interpreted as reflecting lower extraneous cognitive load, as learners experience fewer barriers related to disorientation or poor interface design [50]. Learner performance was operationalized using course activity completions, representing successful engagement with and processing of instructional content [66], and quiz scores for cognitive performance [61].

Media diversity was coded as a binary variable with 0 = text-only content (week one for both groups, and week two for the control group); 1 = media-rich content (week two for the treatment group). This specification enabled clear identification of the moderating role of media diversity in the relationship between extraneous cognitive load and learner performance.

2) Self-reported cognitive load data

To complement the behavioral indicators, learners' perceived cognitive load was collected using a self-reported questionnaire adapted from Leppink *et al.* [45]. The questionnaire was administered at two points: after week 1(pretest) and after week 2 (posttest). The pretest and posttest questionnaires contained conceptually identical items, with item order reshuffled to minimize response bias. The instrument measured multiple components of cognitive load, including Extraneous Cognitive Load (ECL), Intrinsic Cognitive Load (ICL), Germane Cognitive Load (GCL), and Mental Effort (ME). In line with the scope of this study, only the extraneous cognitive load items were analyzed, while the remaining components were collected for completeness and future analysis.

Self-reported ECL scores were computed as the mean of the extraneous load items. The internal consistency of the ECL scale was assessed using Cronbach's alpha, and the questionnaire data were used for triangulation to validate the interpretation of behavioral engagement (course views) as an indicator of extraneous cognitive load.

3) Data analysis strategy

Data analysis followed a two-step approach. First, descriptive statistics were used to summarize learner interaction patterns and baseline equivalence between groups. Second, inferential analysis using mixed-effects moderated regression models was conducted to test the hypothesized relationships between extraneous cognitive load, media diversity, and learner performance while accounting for repeated observations at the learner level. All analyses were conducted in Python using Jupyter Notebook, an open-source environment widely used for statistical modeling [67].

D. How Extraneous Cognitive Load and Learner Performance Were Measured from Moodle Logs

Extraneous Cognitive Load (ECL) and learner performance were operationalized using Moodle log analytics in accordance with the established literature on cognitive load and learning analytics.

Winter [68] argues that behavioral traces recorded in Learning Management Systems (LMS) offer valuable indicators of learners' cognitive processes, with engagement forming a central component in understanding how learners cognitively interact with online instructional materials.

Al-kindi *et al*. [61] define learner engagement as the extent to which a student participates in instructional activities, noting that higher engagement is generally associated with improved cognitive and behavioral learning outcomes.

According to cognitive load theory views, extraneous cognitive load rises when instructional materials impose unnecessary processing demands that impede effective learning [6, 69, 70]. Such demands often lead to disorientation and hinder learners' continued navigation of learning materials [70]. Building on these theoretical insights and recent learning analytics research, including the guidance from the Moodle cognitive depth indicator model [49, 53, 62] and cognitive load theory [8], we conceptualized that learners' engagement, specifically the frequency of their interactions with the course materials, can serve as observable indicators of ECL. In this interpretation, higher engagement (more views) reflects reduced extraneous load, as learners can navigate learning materials more efficiently and sustain purposeful interaction.

To identify appropriate system-recorded indicators for engagement and performance from Moodle LMS, we followed the data structure and measurement guidelines of Al-Kindi *et al*. [61]. Moodle logs contain nine core fields [71], with the *Event name* field being particularly valuable because it records the exact learning activities undertaken [72]. Previous research confirms that these event-level activities reliably reflect learner engagement patterns [73–75], Al-Kindi *et al*. [61] therefore recommend measuring engagement by counting all course activity events associated with each learner.

Based on this guideline, we extracted the key engagement-related events (course module views and course views) from the Event name context fields (see Table A1 in the appendices). Evidence from [74] indicates that course module views have negligible predictive power for learner performance, with regression weights near zero. Guided by this empirical finding, we selected course views as the primary behavioral indicator for ECL-related engagement. In our context, higher engagement (more view counts) thus corresponds to lower extraneous cognitive load, as it indicates more navigation and sustained engagement with course materials.

Performance was operationalized using a dual structure, distinguishing between behavioral and cognitive performance. Behavioral performance was measured through course activity completion counts, which reflect learners' execution of required tasks through viewing or submitting the task [75–77]. Cognitive performance was measured using quiz (exam) scores, a widely accepted indicator of learners' knowledge acquisition and achievement in online learning environments [61]. Table 1 presents a summary of ECL and the performance measurement scale.

Table 1. Extraneous cognitive load and performance measurement scale

Moodle Indicator	Construct	High Count interpretation	Low Count interpretation
Engagement (Course views)	Extraneous load	Low extraneous cognitive load	High extraneous cognitive load
Course activity completions	Behavioral performance	High behavioral performance	Low behavioral performance
Quiz/Test scores	Cognitive performance	High cognitive performance	Low cognitive performance

Overall, the decision of choosing these indicators was informed by Romero's [76] recommendation that learning analytics studies should utilize only the most representative and pedagogically relevant LMS attributes. Finally, this approach addresses the imbalance identified by Henrie [77], noting that many studies rely heavily on self-reported measures instead of behavioral data.

To strengthen the validity of the behavioral operationalization of ECL, Methodological triangulation was employed using self-reported cognitive load measures. The ECL was assessed using the validated questionnaire developed by Leppink [45]. This is a validated instrument that is widely used in measuring cognitive load dimensions [78].

Triangulation was conducted by examining the convergent relationship between learners' behavioral engagement

(course views) and their self-reported extraneous cognitive load scores.

E. Ethical Approval and Informed Consent

This study was approved by the university's ethics review committee (Approval No. NACOSTI/P/23/30310). Informed consent was obtained from all individual participants included in the study. Data confidentiality was maintained through anonymization of student records, and access to the datasets was restricted to the research team. The study adhered to international standards for data protection and research integrity.

To ensure that no learner was academically disadvantaged during the study, both treatment and control groups were provided with identical course content, learning objectives, assessments, and grading criteria within the Moodle learning environment. The experimental manipulation was limited solely to the mode of content presentation: learners in the treatment group accessed media-rich instructional materials incorporating diverse media elements, whereas the control group interacted with text-based materials. This variation was designed to examine differences in media diversity exposure without restricting access to learning opportunities or assessment requirements.

All learning activities were conducted with the same instructional timeframe, with modules opening and closing simultaneously for both groups to ensure equivalent learning conditions. Participation in the program did not influence students' academic progression.

To promote fairness and equitable access, the media-rich instructional interface used in the treatment condition was made available to all learners after the completion of the experimental phase. This approach ensured that no group was denied potential instructional benefits as a result of participation in the study.

IV. Result and Discussion

The purpose of this study was to examine the effects of media diversity on Extraneous Cognitive Load (ECL) and learner performance in online learning, and to determine whether media diversity moderates the relationship between ECL and performance. The results are presented and interpreted in two stages: descriptive and inferential statistics.

A. Descriptive Statistics

The first step of the analysis examined baseline comparability between the treatment and control groups during the initial learning period, when both groups were exposed exclusively to text-based instructional content. Table 2 presents descriptive statistics for engagement (course views), operationalized as a behavioral proxy for extraneous cognitive load, course activity completions (operationalized as a behavioral learner performance), and quiz/test scores (operationalized as a cognitive learner performance) during this baseline learning period.

As shown in Table 2, during the baseline period, the results indicate that both groups exhibited broadly comparable engagement (course views-treatment: Mean = 12.99, Std Dev. = 14.30; control: Mean = 11.84, Std Dev. = 11.54), activity completions (treatment: Mean = 12.47, Std Dev. = 13.86; control: Mean = 12.89, Std Dev. = 12.00), and quiz scores (treatment: Mean = 9.76, Std Dev. = 13.47; control: Mean = 7.67, Std Dev. = 10.89), suggesting that the groups were well balanced before the introduction of media-diverse instructional content.

Table 2. Descriptive statistics during the baseline learning period

Indicator	Treatment Group		Control Group	
	Mean	Std Dev.	Mean	Std Dev.
Engagement (Course Views)	12.99	14.30	11.84	11.54
Course Activity Completions	12.47	13.86	12.89	12.00
Quiz/Test scores	9.76	13.47	7.67	10.89

Following the intervention, the treatment group was exposed to media-diverse content, while the control group continued with text-only content. Table 3 presents the descriptive statistics analysis results from this phase.

Table 3. Descriptive statistics during the media diversity learning period

Indicator	Treatment Group		Control Group	
	Mean	Std Dev.	Mean	Std Dev.
Engagement (Course Views)	7.32	8.24	7.84	8.54
Course Activity Completions	11.22	12.20	7.42	6.45
Quiz scores	4.91	9.85	7.54	10.53

As shown in Table 3, differences emerged across all the indicators. The treatment group displayed distinct means across engagement (course views), course activity completions, and quiz scores, relative to the control group, reflecting changes in interaction behavior and performance following exposure to media diversity.

While descriptive statistics provide an initial overview of engagement (course views), behavioral performance, and cognitive performance across treatment and control groups, they do not indicate whether the observed differences are statistically meaningful or attributable to media diversity. To formally test the study hypotheses and examine the relationships among extraneous cognitive load, media diversity, and learner performance, inferential analyses were therefore conducted. Specifically, mixed-effects linear regression models were employed to account for repeated observations at the learner level and to assess (i) the direct effect of engagement (course views) on performance outcomes, (ii) the direct effect of media diversity, and (iii) the moderating role of media diversity on the relationship between extraneous cognitive load and performance.

B. Inferential Statistics and Hypothesis Testing

In accordance with the methodology described in the methods section, mixed-effects linear regression models were estimated to examine the moderating role of Media Diversity (MD) on the relationship between extraneous cognitive load, operationalized through learner engagement (course views), and performance outcomes. Two outcome variables were analyzed separately to assess the robustness of the proposed moderation model across distinct learning outcomes: behavioral performance, measured by course activity completions, and cognitive performance, measured by quiz/exam scores.

All models included fixed effects for Time (week), Engagement (course views), Media Diversity, and their

corresponding interaction terms. Random intercepts were specified at the learner level to account for between-learner heterogeneity and within-learner dependence arising from repeated observations. Engagement (course views) and media diversity were mean-centered before constructing interaction terms to reduce multicollinearity and facilitate interpretation. All mixed-effects models converged successfully. In both outcome models, random intercept variances were greater than zero, indicating meaningful between-learner variability and justifying the use of multilevel modeling.

1) Media diversity effects on extraneous cognitive load and learner behavioral performance (mixed-effects behavioral performance model results)

Table 4 presents the mixed-effects regression results for behavioral performance (course activity completions). Learner engagement (course views) exhibited a positive and statistically significant association with behavioral performance ($\beta = 0.518$, $p < 0.001$), indicating that higher levels of engagement (course views), interpreted in this study as lower extraneous cognitive load, were associated with increased completion of learning activities.

Table 4. Media diversity effects on extraneous cognitive load and behavioral performance (mixed-effects model results)

Predictor	β (Estimate)	SE	Z	p-value	95% CI
Intercept (β_0)	1502.35	6.39×10^7	0.000	1.000	$[-1.25 \times 10^8, 1.25 \times 10^8]$
Time	−1492.25	6.39×10^7	−0.000	1.000	$[-1.25 \times 10^8, 1.25 \times 10^8]$
Engagement (course views)	0.518	0.027	18.93	0.000	[0.464, 0.572]
Media Diversity	6345.10	2.72×10^7	0.000	1.000	$[-5.33 \times 10^7, 5.33 \times 10^7]$
Time × Media Diversity	−6344.00	2.72×10^7	−0.000	1.000	$[-5.33 \times 10^7, 5.33 \times 10^7]$
Engagement × Media Diversity	−0.239	0.047	−5.10	0.000	[−0.331, −0.147]
Random Effect (Group Var.)	9.313	-	-	-	-

Media diversity did not show a statistically significant direct effect on behavioral performance. However, the interaction between engagement (course views) and media diversity was negative and statistically significant ($\beta = -0.239$, $p < 0.001$), indicating that media diversity moderated the relationship between engagement and behavioral performance. While higher engagement (course views) (implying low extraneous load in our context) was generally associated with better behavioral performance, the magnitude of this positive association was attenuated under conditions of higher media diversity. This pattern suggests that increased media richness may introduce additional extraneous cognitive load, thereby weakening the performance benefits typically associated with learner engagement.

Neither the main effect of Time nor the Time × Media Diversity interaction reached statistical significance. This likely reflects limited within-learner temporal variation, as many learners contributed a single observation across the study period, constraining the estimability of time-related effects within the mixed-effects framework. Consequently, interpretation focused primarily on engagement-based effects and moderation effects, which were consistently identifiable. The random intercept variance (Group Var = 9.313) indicated a substantial between-learner difference in behavioral performance beyond what was explained by the fixed effects.

To visualize the interaction between engagement (course views) and media diversity and their relationship with behavioral performance, simple slopes analyses were conducted at low (−1 SD), mean, and high (+1 SD) levels of media diversity. As shown in Fig. 2, at low levels of media diversity (−1 SD), engagement exhibited the strongest positive association with behavioral performance ($\beta = 0.619$), indicating that the instructional media were relatively less; increases in engagement were most effective in translating into higher course activity completion. At the mean level of media diversity, this positive relationship weakened ($\beta = 0.518$), while at high media diversity (+1 SD), the slope further reduced ($\beta = 0.416$).

This progressive reduction in slope magnitude indicates that although engagement remained a positive predictor of behavioral performance across conditions, increasing media diversity systematically weakened the performance gains associated with engagement. This suggests that richer or more complex media environments may introduce additional extraneous cognitive load, limiting learners' ability to convert engagement into effective task completion.

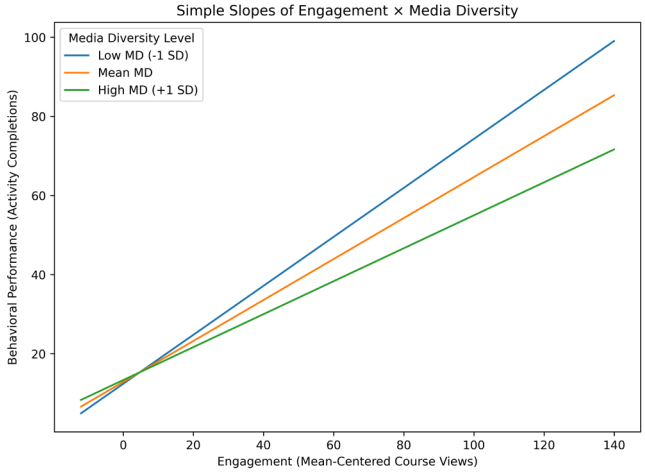

Fig. 2. Simple slopes plot illustrating the moderating effect of media diversity on the relationship between learner engagement (course views) and behavioral performance.

2) Media diversity effects on extraneous cognitive load and learner cognitive performance (mixed-effects cognitive performance model results)

Results for the cognitive performance model are reported in Table 5. Consistent with the behavioral performance findings, learner engagement showed a positive and statistically significant association with cognitive performance ($\beta = 0.409$, $p < 0.001$), indicating that higher engagement (lower extraneous cognitive load) was associated with improved quiz scores.

Media diversity did not exhibit a significant direct effect on cognitive performance. However, the interaction between engagement and media diversity was negative and statistically significant ($\beta = -0.195$, $p < 0.001$), confirming that media diversity moderated the engagement-cognitive performance relationship. Similar to the behavioral

performance, higher levels of media diversity reduced the strength of the positive association between engagement and quiz performance, suggesting that excessive media richness may interfere with learning processes that support knowledge acquisition.

Table 5. Media diversity effects on extraneous cognitive load and cognitive performance (mixed-effects model results)

Predictor	β (Estimate)	SE	Z	p-value	95% CI
Intercept (β_0)	−257.721	1.79×10^7	−0.000	1.000	$[-3.51 \times 10^8, 3.51 \times 10^8]$
Time	264.877	1.79×10^7	0,000	1.000	$[-3.51 \times 10^8, 3.51 \times 10^8]$
Engagement (course views)	0.409	0.029	13.91	0.000	[0.351, 0.466]
Media Diversity	−1130.498	7.62×10^7	−0.000	1.000	$[-1.49 \times 10^7, 1.49 \times 10^7]$
Time x Media Diversity	1132.138	7.62×10^7	0.000	1.000	$[-1.49 \times 10^7, 1.49 \times 10^7]$
Engagement x Media Diversity	−0.195	0.05	−3.88	0.000	[−0.294, −0.097]
Random Effect (group Var.)	9.560	-	-	-	-

The main effect of Time and its interaction with media diversity (Time × Media Diversity) were not statistically significant in this model as well, reflecting similar data-structure limitations observed in the behavioral performance analysis. Although time (week) was included as a fixed effect to reflect the study design, its interpretability is limited because a substantial proportion of learners contributed only a single observation, restricting within-learner temporal variance and statistical power to detect time-related effects. Consequently, interpretation focuses primarily on engagement-based effects and interaction terms, which were consistently estimable. The random intercept variance (Group Var = 9.560) indicated notable between learner variability in cognitive performance, comparable to that observed for behavioral performance (Group Var = 9.313).

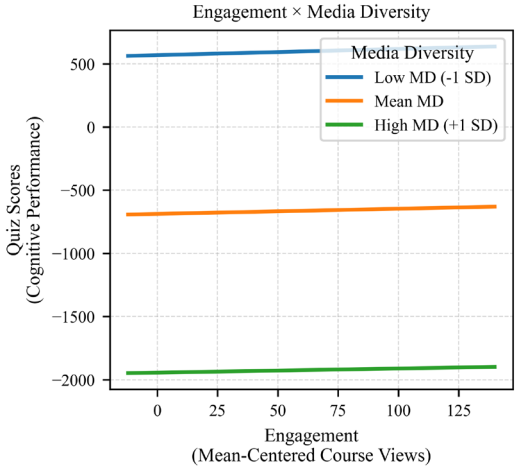

Fig. 3. Simple slopes plot illustrating the moderating effect of media diversity on the relationship between learner engagement (course views) and cognitive performance.

Finally, to visualize the interaction between engagement (course views) and media diversity and their relationship with cognitive performance, a simple slopes analysis was conducted. Fig. 3 shows a parallel pattern that was observed for cognitive performance. Engagement (course views) was strongly related to quiz performance at low media diversity ($\beta = 0.491$), followed by a reduced effect at the mean level of media diversity ($\beta = 0.409$), and the weakest association under high media diversity conditions ($\beta = 0.326$). The consistency of this attenuation across both behavioral and cognitive outcomes reinforces the moderating role of media diversity.

3) Sensitivity and robustness of findings

Analyzing both behavioral and cognitive performance outcomes yielded substantively consistent results. Across both models, learner engagement (course views) emerged as a strong predictor of performance, while media diversity functioned as a moderator rather than a direct determinant of learning outcomes. Importantly, the direction and statistical significance of the Engagement (course views) × Media Diversity interaction were consistent across outcome measures, supporting the robustness of the moderation effect.

These findings suggest that although higher engagement (reflecting low extraneous load) generally enhances both behavioral and cognitive learning outcomes, excessive media diversity may introduce extraneous cognitive load that weakens the performance benefits associated with engagement.

4) Triangulation and validation of extraneous cognitive load measures

To strengthen the validity of learner engagement (course views) as a behavioral indicator of Extraneous Cognitive Load (ECL), a triangulation analysis was conducted using learners' self-reported ECL collected at pretest (week 1) and posttest (week 2). In line with cognitive load research, higher engagement was interpreted as indicative of lower extraneous cognitive load, while reduced engagement reflected increased extraneous load. Given the non-normal distribution of the data, non-parametric tests were employed throughout the triangulation analyses. Cronbach's alpha was computed to assess the reliability of the self-reported ECL scale.

a) Within-treatment validation using self-reported ECL

A within-treatment analysis examined whether exposure to media-diverse instructional materials resulted in a measurable change in perceived extraneous cognitive load. As illustrated in Fig. 4, the box plot shows an increase in median self-reported ECL from pretest to posttest, accompanied by an upward shift in the Interquartile Range (IQR). This pattern indicates that learners reported higher levels of extraneous cognitive load after interacting with media-diverse content.

A Wilcoxon signed-rank test conducted on paired pretest to posttest self-report data from the treatment group confirmed this observation, revealing a statistically significant increase in extraneous cognitive load from pretest to posttest ($p = 0.005$). Because all learners had prior knowledge of a prerequisite course (advanced web application development delivered online), thereby controlling for baseline knowledge differences, this increase in perceived extraneous cognitive load was attributable to the instructional intervention rather than pre-existing learner characteristics.

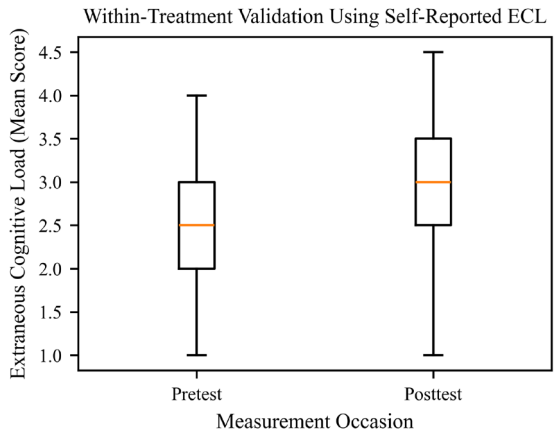

Fig. 4. Pretest to posttest self-reported ECL scores within the treatment group.

b) Between-group post-test validation using self-reported ECL

Between-group comparisons of post-test self-reported ECL further supported the within-treatment findings. As shown in Fig. 5, learners in the treatment group exhibited a higher median self-reported ECL than those in the control group. A Mann-Whitney U test confirmed that this difference was statistically significant (Mann–Whitney U = 1191.5, $p = 0.002$), indicating that learners exposed to media-diverse instructional materials experienced higher perceived extraneous cognitive load at posttest. The internal consistency of the two-item self-reported ECL scale was acceptable (Cronbach's $\alpha = 0.673$). Given that the scale was used for exploratory triangulation rather than as a standalone psychometric measure, this level of reliability is consistent with previous cognitive load research employing short instruments.

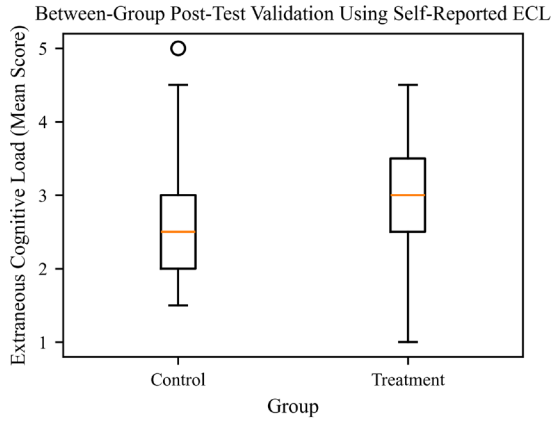

Fig. 5. Post-test self-reported ECL scores between-groups.

c) Between-group post-test validation using behavioral engagement (course views)

Behavioral triangulation was conducted using Moodle engagement data, operationalized as course views. Lower engagement was interpreted as reflecting higher extraneous cognitive load, consistent with learning analytics research suggesting that disorientation or overload reduces meaningful interaction with learning materials. Fig. 6 presents the posttest comparison, showing that the treatment group exhibited a lower median level of engagement (course views) and IQR relative to the control group.

A Mann-Whitney U test comparing engagement levels between groups at week 2 revealed a highly statistically significant difference ($p < 0.001$), indicating that learners in the media-diverse condition displayed distinct engagement patterns consistent with increased extraneous cognitive load. This behavioral evidence corroborates both the self-reported ECL findings and the moderation effects observed in the mixed-effects model, where media diversity reduced the positive relationship between engagement (course views) and performance.

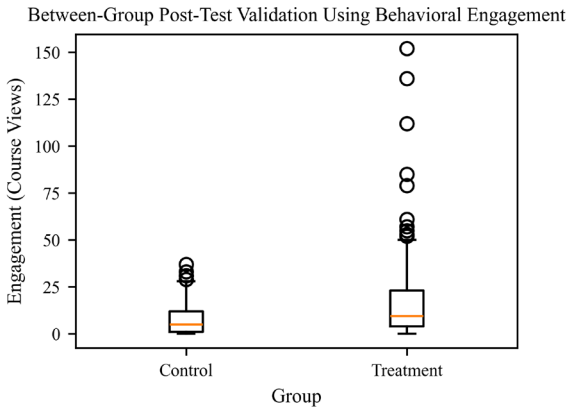

Fig. 6. Post-test behavioral engagement between groups.

d) Convergence across behavioral and subjective measures

These triangulation results demonstrate convergent evidence across behavioral and subjective measures of extraneous cognitive load. The statistical significance in the within-treatment analysis revealing an increase in self-reported extraneous cognitive load at post-test, combined with notable post-test differences in both behavioral engagement and self-report ECL between groups, supports the interpretation that media diversity increased learners' extraneous cognitive load during the post-intervention phase. This convergence validates the use of engagement (course views) as a meaningful behavioral proxy for extraneous cognitive load in Moodle-based learning environments and strengthens confidence in the moderation analyses linking engagement, media diversity, and learner performance.

5) Summary of hypothesis testing

a) H01: There is no significant relationship between extraneous cognitive load and learner performance

This hypothesis was rejected. Learner engagement (course views), interpreted as an inverse indicator of extraneous cognitive load, was positively and significantly associated with both behavioral performance ($\beta = 0.518$, $p < 0.001$) and cognitive performance ($\beta = 0.409$, $p < 0.001$).

b) H02: There is no significant relationship between media diversity and learner performance

This hypothesis was rejected. Media diversity did not exhibit a statistically significant direct effect on either behavioral or cognitive performance across models ($p > 0.05$).

c) H03: Media diversity does not significantly moderate the relationship between extraneous cognitive load and learner performance

This hypothesis was rejected. The interaction between

engagement (course views) and media diversity was negative and statistically significant for both behavioral performance ($\beta = -0.239$, $p < 0.001$) and cognitive performance ($\beta = -0.195$, $p < 0.001$), indicating a moderation effect.

V. Discussion

The goal of this study was to examine how media diversity influences Extraneous Cognitive Load (ECL) and learner performance in online learning environments, and whether it moderates the relationship between them. Findings from this investigation provide compelling evidence that learner engagement, operationalized through course views as a behavioral indicator of ECL, is a strong predictor of both behavioral and cognitive performance outcomes.

The inferential analyses revealed a positive and significant relationship between engagement (course views) and performance. Higher levels of engagement were associated with increased course activity completions and higher quiz scores, confirming that efficient navigation and interaction with learning materials correspond to reduced extraneous cognitive load and improved learning outcomes. This finding is consistent with Cognitive Load Theory, which posits that minimizing unnecessary processing demands allows learners to allocate cognitive resources toward schema construction and task execution [79].

Before interpreting the substantive effects, it is important to clarify the role of time in the analysis. Although time (week) was included as an affixed effect to reflect the study design, its interpretability is limited because a substantial proportion of learners contributed only a single observation, restricting within-learner temporal variance and statistical power to detect time-related effects. Accordingly, interpretation focuses primarily on engagement-based effects and interaction terms, which were consistently estimable.

Contrary to some expectations in multimedia learning research, such as the arguments by Mayer *et al.* [16], Mayer and Fiorella [80], and Kalyuga and Sweller [81] that media resources can enhance engagement and facilitate comprehension by supporting dual coding and multiple representations of information, media diversity did not exert a significant direct effect on either behavioral or cognitive performance. This suggests that the mere presence of multiple media formats does not automatically enhance learning outcomes. Instead, its effects depend on how it interacts with learners' cognitive processing [28].

Critical to our investigation, the results demonstrated a significant negative moderating effect of media diversity on the engagement (course views)-performance relationship. Simple slopes analyses showed that although engagement (course views) remained positively associated with performance across all conditions, the strength of this relationship weakened as media diversity increased. This pattern indicates that higher media diversity increased extraneous cognitive load, thereby reducing the performance gains associated with increased engagement (course views).

Triangulation with subjective measures of extraneous cognitive load reinforced this interpretation. Learners exposed to media-diverse content reported significantly higher extraneous cognitive load and exhibited lower behavioral engagement (course views) compared to those in the text-only condition. The convergence of Moodle-based behavioral engagement (course views), behavioral and cognitive performance measures (course activity completions and quiz scores), and self-reported extraneous cognitive load ratings provides robust evidence that excessive or poorly aligned media diversity can impose additional cognitive demands.

These findings align with the redundancy and split-attention effects described in previous Cognitive Load Theory research, emphasizing that instructional design must balance media richness with cognitive simplicity [9, 34, 81].

VI. Conclusion

This study aimed to investigate whether media diversity moderates the existing relationship between extraneous cognitive load and learner performance in online learning environments based on cognitive load theory optics. Using Moodle log data, self-reported cognitive load measures, and mixed-effects regression models, the findings reveal that media diversity significantly influenced how extraneous cognitive load affected learners' performance.

The results showed that media diversity does not directly improve learner performance. Instead, it significantly moderates the extraneous cognitive load-performance relationship in a negative direction, such that increased media diversity elevates extraneous cognitive load and weakens learner performance. Overall, the study demonstrates that extraneous cognitive load is a strong predictor of learner performance, while media diversity plays a conditional role, rather than a direct role, by moderating this relationship. These findings confirm that media diversity must be strategically designed rather than indiscriminately applied.

By integrating behavioral analytics with subjective cognitive load measures, this study provides empirical support for Cognitive Load Theory in digital learning contexts and highlights the importance of cognitively informed instructional design. The results underscore that learning outcomes are shaped not only by learner engagement but also by how instructional media interact with cognitive processing demands.

From a practical perspective, the findings suggest that media diversity should be applied strategically rather than maximized indiscriminately. Educators and instructional designers should prioritize coherence, relevance, and cognitive alignment when incorporating multiple media formats. Specifically, cognitively informed media design principles grounded in Cognitive Load Theory should guide LMS-based instructional design. For example, designers should avoid redundant multimedia presentations, such as narrated text displayed verbatim on screen, which can increase extraneous cognitive load through redundancy effects. Media elements should be sequenced progressively rather than presented simultaneously, and visual and verbal materials should be aligned spatially and temporally to minimize split attention and unnecessary processing demands. Learning management systems such as Moodle can further support cognitively informed design by leveraging learning analytics to identify disengagement patterns and adapt media presentation dynamically, thereby enabling real-time monitoring and management of extraneous cognitive load. Collectively, these principles support the development of media-rich yet cognitively supportive online

learning environments.

In general, the study contributes to theory by advancing understanding of media diversity as a conditional, rather than inherently beneficial, design element in online learning. By empirically demonstrating its moderating role in the relationship between engagement-related extraneous cognitive load and learner performance, the study extends previous research on multimedia learning and cognitive load theory. Furthermore, it provides a foundation for future research examining how learner characteristics, adaptive media strategies, and learning analytics-driven interventions can be integrated to further optimize online learning environments.

APPENDIX

Table A1. Moodle log file showing engagement-related events

User Full Name	Event Context	Component	Event Name
std1	Course: Laravel PHP Framework (TC)	System	Course viewed
std1	Course: Laravel PHP Framework (TC)	System	Course viewed
std1	Course: Laravel PHP Framework (TC)	System	Course viewed
std2	Course: Laravel PHP Framework (TC)	System	Course viewed
std2	Quiz: Lesson One Quiz	System	Course activity completion updated
std2	Quiz: Lesson One Quiz	System	Course activity completion updated
Std3	Quiz: Lesson One Quiz	Quiz	Course module viewed
Std3	File: Lesson One Notes	File	Course module viewed
Std3	Course: Laravel PHP Framework (TC)	System	Course viewed

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Thaddeus Ogwoka reviewed the literature, conceptualized and designed the study, developed the research instruments, carried out the experiment, oversaw data collection, performed the data analysis, interpreted the results, drafted the methodology and results sections, and prepared the initial manuscript draft. Robert Oboko contributed to conceptualizing and designing the study, contributed to the drafting of the methodology, interpreted the results, and coordinated revision of the final manuscript draft. Christopher Chepken contributed to conceptualizing and designing the study, contributed to the drafting of the methodology, interpreted the results, and revised the draft manuscript. All authors read and approved the final version.

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