Development of Interactive E-Modules Based on Blender 3D Visualization: Analysis of Extraneous Cognitive Load and Its Effectiveness on Learning Outcomes

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ABSTRACT

The growing demand for technology-based learning media has encouraged the development of interactive e-modules with three-dimensional visualization. However, poorly designed 3D media may increase extraneous cognitive load (ECL) and hinder students' understanding. This study offers novelty by developing a 3D Blender-based interactive e-module designed with cognitive load management principles, particularly to minimize ECL while improving learning outcomes. The study aimed to develop the e-module and evaluate its impact on students' cognitive load and achievement. This research used the Research and Development (R&D) method with the ADDIE model. The implementation involved 48 students at the University of Education Indonesia selected through purposive sampling using a one-group pretest-posttest design. Cognitive load was measured using a nine-item psychological scale questionnaire covering ICL, ECL, and GCL, while learning outcomes were assessed using a 15-item multiple-choice test. Data were analyzed descriptively and inferentially using the Shapiro-Wilk normality test and the Wilcoxon Signed Rank Test. The results showed that students' ECL was low ($\bar{x} = 2.09$), indicating that the e-module did not overload working memory. Learning outcomes increased significantly from 34.67% to 84.67% ($p = 0.000002$). These findings indicate that the proposed e-module effectively supports conceptual understanding while reducing unnecessary cognitive load.

Keywords: Interactive E-Module; 3D visualization; Extraneous Cognitive Load; Learning Outcomes; Blender 3D

1. INTRODUCTION

The development of digital technology has encouraged the transformation of learning media to be more interactive, flexible, and adaptive to the needs of students (Zou et al., 2025). According to Mhlongo et al., (2023), more than 85% of higher education institutions globally have integrated digital learning media into their instructional practices, reflecting the accelerating pace of educational technology adoption. One of the innovations that is developing is an interactive e-module that is able to integrate various multimedia elements in a single learning unit (Liunima et al., 2025). Previous research has shown that interactive e-modules can increase motivation, understanding of concepts, and learning independence compared to conventional teaching materials (Abdamia et al., 2023). However, many of these studies were conducted using text- and image-based e-modules that rely on static two-dimensional representations, which are considered less effective for materials requiring spatial understanding (El-Husseiny et al., 2025). Furthermore, the instructional designs employed frequently overlook cognitive load management principles, resulting in suboptimal learning experiences, particularly for students with limited prior knowledge (Li et al., 2025).

In the perspective of Cognitive Load Theory (CLT), inefficient learning design can increase extraneous cognitive load (ECL), which is the cognitive load that arises as a result of presenting irrelevant or confusing information (Li et al., 2025). This burden has the potential to hinder information processing and degrade the quality of understanding (Tang et al., 2026). Therefore, the design of learning media needs to be directed to minimize ECL so that cognitive capacity can be focused on understanding concepts.

Along with the development of immersive technology, the use of 3D visualization in learning shows significant potential, but it also presents challenges related to cognitive load. Studies show that VR-based environments can improve ECL and inhibit learning outcomes if not designed well, especially for beginners (Ciardo et al., 2022; De Witte et al., 2026). These studies highlight a critical limitation: immersive 3D environments without structured instructional scaffolding tend to overwhelm novice learners rather than support them, raising questions about how 3D elements should be integrated within conventional e-module formats. In contrast, a structured AR/MR approach can lower cognitive load and improve learning performance (Buchner et al., 2022; Zhu et al., 2026). This effectiveness is greatly influenced by instructional design, such as simplifying visual elements, providing attention guidance, and segmentation of materials (Liu, 2024), as well as the quality of system interactions that are able to suppress ECL and improve learning outcomes (Yin & Sun, 2026).

In materials that require spatial visualization, 3D-based media is a potential solution because it is able to present a more concrete representation of objects than two-dimensional visuals (El-Husseiny et al., 2025; Han et al., 2025). The use of 3D visualization has also been proven to improve students' understanding of concepts and learning outcomes (Schirone et al., 2024; Suhail et al., 2024). In this context, Blender 3D software allows for the development of more interactive and representative learning media, thus potentially reducing ECL due to inefficient design (Sari et al., 2022; Zhu et al., 2026). Several studies have demonstrated the educational potential of Blender 3D across disciplines: Sari et al., (2022) found that Blender-based 3D animations significantly enhanced spatial reasoning in engineering students; (J. D. Nascimento Júnior et al., 2026) reported improved conceptual understanding when Blender-rendered models were embedded in science learning modules. Despite these promising results, existing studies on Blender-based e-modules have largely focused on content presentation quality without empirically measuring the impact on students' extraneous cognitive load, leaving a gap between instructional design recommendations and measurable cognitive outcomes.

Despite growing evidence supporting the use of 3D visualization in education, a notable gap remains: few studies have empirically examined how 3D visualization-based e-modules, particularly those developed using Blender 3D, affect students' extraneous cognitive load in a controlled instructional setting. Most existing research either focuses on immersive environments (VR/AR) without translating findings to accessible e-module formats or evaluates learning outcomes without directly measuring cognitive load as a mediating variable. This gap limits educators' ability to design evidence-based 3D learning media that are both cognitively efficient and pedagogically effective. This study contributes to the field by providing empirical evidence on how CLT-informed 3D visualization, implemented within an accessible e-module format, can simultaneously reduce extraneous cognitive load and improve learning outcomes, offering actionable design principles for educators and instructional designers working with 3D-based digital media. The focus on Blender 3D as a practical and widely available tool also extends prior research by bridging the gap between high-end immersive environments and classroom-ready learning media. (RQ1) How is the level of extraneous cognitive load (ECL) of students when using interactive e-modules based on 3D visualization, and (RQ2) whether the use of these e-modules can improve students' learning outcomes, both of which are grounded in the identified gap between 3D instructional design practice and measurable cognitive outcomes.

2. RESEARCH METHOD

2.1. Research Design

This study applied the Research and Development (R&D) method with the ADDIE model, which consists of Analysis, Design, Development, Implementation, and Evaluation stages. The selection of the ADDIE model was based on its systematic and iterative characteristics, allowing evaluation at each stage to ensure the quality of the e-module product before wider implementation (Suherti et al., 2023). The implementation of the product was carried out using a one-group pretest-posttest design, in which one group of participants was measured before and after the intervention without a comparative control group. This design was considered appropriate because the study focused on the initial implementation and formative evaluation of the developed e-module rather than on establishing strong causal claims. Through this design, changes in students' learning outcomes before and after using the e-module could be identified directly within the same group of participants. However, the absence of a control group limits the ability to fully control external factors, such as maturation, testing effects, or other learning experiences outside the intervention. Therefore, the findings should be interpreted as evidence of preliminary effectiveness and should be strengthened in future studies using a control group or quasi-experimental design.

Participants in the field trial involved 48 university students in Purwakarta. The sample was determined through a purposive sampling technique with three inclusion criteria: (1) active registered students; (2) having access to compatible digital devices, such as gadgets or laptops; and (3) having never received the specific material developed in this study, in order to minimize prior knowledge bias in measuring the effectiveness of the module.

2.2. Development Procedure

The Analysis stage begins with a needs assessment activity to map the gap between the current availability of learning media and the expected learning outcomes. This process is continued with curriculum analysis to formulate basic competencies and achievement indicators, and ends with an analysis of student characteristics to determine the 3D visualization style that best suits students' cognitive levels.

The Design stage includes designing media blueprints based on the results of the analysis. The design is laid out in a flowchart to illustrate the flow of navigation as well as a storyboard for the visual layout. The main focus at this stage is designing an intuitive user interface with the goal of minimizing ECL when interacting with 3D objects.

The Development stage is the process of realizing the design into a functional e-module product. All three-dimensional visual assets are modeled, textured, and rendered using Blender 3D software, then integrated into a single interactive media unit. Product prototypes are validated by subject matter experts and media experts before entering the field trial phase (Mawarni & Hendriyani, 2021). The Implementation phase is carried out using a one-group pretest-posttest design. Respondents took the pre-test, then used the e-module independently, filled out a cognitive load questionnaire, and did a post-test after the learning session was over.

The validation process was conducted by one expert validator who assessed the e-module using a structured rubric covering eight aspects, rated on a scale of 1 to 5. An aspect is categorized as "Eligible" if the score reaches ≥ 3.40 (≥ 68%), and "Needs Revision" if the score falls below that threshold. The results of the expert validation are presented in Table 2a below.

Table 1. Expert Validation Results

No.	Validation Aspect	Score (1–5)	Category
1	Accuracy and correctness of content	4	Eligible
2	Alignment with learning objectives and competencies	4	Eligible
3	Clarity of textual explanations accompanying 3D visuals	3	Needs Revision
4	Suitability of examples and practice exercises	4	Eligible

No.	Validation Aspect	Score (1–5)	Category
5	Visual design quality and color contrast	3	Needs Revision
6	Ease of navigation and interface usability	4	Eligible
7	Quality and clarity of 3D visualization rendering	5	Eligible
8	Interactivity and multimedia integration	4	Eligible

Scoring scale: 1–5. Eligible: score ≥ 3.40; Needs Revision: score < 3.40.

Based on Table 1, six out of eight validation aspects were categorized as "Eligible," while two aspects, namely the clarity of textual explanations accompanying 3D visuals (aspect 3, score = 3) and the visual design quality and color contrast (aspect 5, score = 3) were categorized as "Needs Revision." The expert noted that the text accompanying the 3D visualizations was insufficiently detailed to support independent learning and that several interface elements had low color contrast, potentially hindering readability. In accordance with the expert's recommendations, revisions were made to the e-module prototype before it was implemented in the field trial phase. These revisions specifically addressed the two underperforming aspects: the accompanying texts were rewritten to be more explanatory and aligned with each 3D object view, and the color scheme of the interface was adjusted to improve contrast and visual accessibility. Only after these revisions were confirmed to address the validator's feedback was the e-module considered ready for implementation with the target participants.

The Evaluation stage is carried out formatively in each phase of development and summative based on the results of empirical data analysis from the implementation, which will be discussed in the Results and Discussion section.

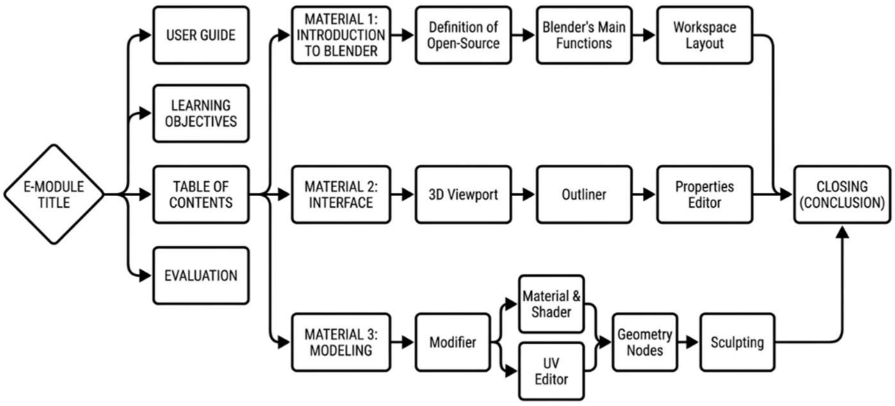

Figure 1. Development Flow

2.3. Data Collection Instruments and Techniques

The data collection instrument was specifically prepared to answer both formulations of the research problem. To answer RQ1 related to Extraneous Cognitive Load (ECL), data were collected using a psychological scale questionnaire (Subjective Rating Scale) adapted from the cognitive load measurement scale by Hollender et al. (2010) (DOI: https://doi.org/10.1016/j.chb.2010.05.031). The instrument consists of 9 items that measure three aspects of cognitive load, namely Intrinsic Cognitive Load (ICL), Extraneous Cognitive Load (ECL), and Germane Cognitive Load (GCL), using a Likert scale of 1–5. Respondents fill out a questionnaire immediately after the learning session. To answer RQ2 related to learning outcomes, the instrument used was a multiple-choice objective test of 15 questions given in two terms: pre-test (before intervention) and post-test (after intervention).

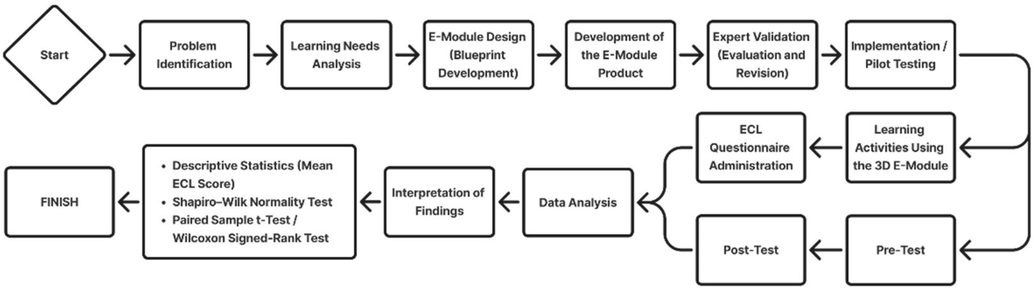

Figure 2. Data collection techniques

Figure 2 shows the sequence of data collection techniques in this study, starting from problem identification and learning needs analysis to the design, development, validation, implementation, and evaluation of the 3D Blender-based interactive e-module. In the implementation stage, students completed a pre-test before using the e-module to measure their initial learning outcomes. After participating in learning activities using the 3D e-module, students completed a post-test and filled out the ECL questionnaire. The collected data were then analyzed through descriptive statistics, the Shapiro-Wilk normality test, and either the paired sample t-test or the Wilcoxon Signed-Rank Test, depending on the distribution of the data. The results of the analysis were subsequently interpreted to formulate the research findings.

Table 2. Research Instruments

Yes	Variabel	Instruments	Aspects	Ref
1	Extraneous Cognitive Load (RQ1)	Cognitive Load Psychological Scale Questionnaire (9 items, Likert 1–5)	ICL, ECL, GCL	Hollender et al. (2010)
2	Learning Outcomes (RQ2)	Multiple Choice Test (15 items, pre-test & post-test)	Cognitive	Researcher Development

Table 1 summarizes the instruments used in this study according to the research questions. To answer RQ1, students' cognitive load was measured using a psychological scale questionnaire consisting of nine Likert-scale items adapted from Hollender et al. (2010). This instrument covered three aspects of cognitive load: Intrinsic Cognitive Load, Extraneous Cognitive Load, and Germane Cognitive Load. Meanwhile, to answer RQ2, students' learning outcomes were measured using a 15-item multiple-choice test developed by the researcher. The test was administered as both a pre-test and a post-test to identify changes in students' cognitive achievement before and after learning with the 3D e-module.

2.4. Data Analysis Techniques

Data analysis was carried out descriptively and inferentially. For RQ1, ECL data is analyzed by calculating the mean score of each item and per aspect. The ECL item score (items 4–6) is positive so that reverse scoring is performed before the calculation of the average ECL aspect, using the formula: $reversed\_score = (maximum\_score + 1) - original\_score = 6 - original\_score$. The average ECL is then categorized by interval with class width = (5 – 1) / 5 = 0.80.

For RQ2, the analysis begins with descriptive statistics (mean, minimum, maximum, standard deviation) of pre-test and post-test scores converted to a percentage scale (0–100). Furthermore, a Shapiro-Wilk normality test was performed (chosen because n = 48) with significance levels. If both data groups are normally distributed, hypothesis testing uses the Paired Sample T-Test; if one or both are abnormal, the Wilcoxon Signed Rank Test is used. The hypotheses tested are:$\alpha = 0{,}05 (p > 0{,}05)$

Table 3. Research Hypothesis

H_0	There was no significant difference in learning outcomes before and after the use of e-modules
H_1	There was a significant improvement in learning outcomes after the use of e-modules. The decision is taken based on the value of p: if $p < 0.05$ then H_0 is subtracted.

3. RESULT AND ANALYSIS

3.1. ECL Measurement Results

Cognitive load data was collected from 48 respondents using a 9-item questionnaire that measured three aspects of cognitive load. Table 2 presents the average score of each cognitive load instrument item.

Table 4. Average Score of Each Cognitive Load Instrument Item

No.	Aspects	Statement (Item)	Average
1	ICL	The concept of material presented in this e-module is classified as difficult/complex.	3,27
2	ICL	I had to think hard to understand the definition and core of the material in this module.	3,10
3	ICL	This subject matter contains many terms or concepts that are complicated for me.	2,93
4	ECL	The explanations of the text that accompany the 3D visualization are presented very clearly.	3,87
5	ECL	The 3D visual display (Blender) helps me visualize the shape of objects easily.	4,07
6	ECL	The button layout and e-module navigation don't confuse me while learning.	3,80
7	GCL	The 3D visualization made me more motivated to understand the material in depth.	3,73
8	GCL	I tried to connect the 3D object view with the knowledge I already had.	3,60
9	GCL	This e-module helped me construct a more complete understanding of the subject matter.	3,87

Note: Item scores 4–6 (ECL) are positive; a higher value indicates a lower ECL.

Cognitive load data were collected from 48 respondents using a nine-item questionnaire that measured three aspects of cognitive load, namely Intrinsic Cognitive Load (ICL), Extraneous Cognitive Load (ECL), and Germane Cognitive Load (GCL). Table 3 presents the average score of each cognitive load instrument item. In addition to the cognitive load questionnaire, learning outcomes were measured using a 15-item multiple-choice test administered as a pre-test and post-test. It can be seen that the average score on the ICL aspect (items 1–3) is in the range of 2.93–3.27, which indicates that most respondents feel a level of material complexity in the medium category. Meanwhile, in the ECL aspect (items 4–6), the average score was relatively high (3.80–4.07), which indicates that the visualization and navigation design of the e-module is considered clear and helps the learning process. In the GCL aspect (items 7–9), Before being used in the field trial, the learning outcome test instrument underwent validity and reliability testing to ensure its appropriateness in measuring students' cognitive achievement. The validity test was conducted to examine whether each item represented the intended learning indicators, while the reliability test was conducted to determine the consistency of the instrument. Based on these procedures, the final learning outcome test was considered feasible for use in measuring students' achievement before and after the intervention.

Table 5. Average per Aspect of Cognitive Load

Aspects	Item	Average	Category
ICL (Intrinsic Cognitive Load)	1, 2, 3	3,10	Medium
ECL (Extraneous Cognitive Load)	4, 5, 6*	2,09	Low
GCL (Germane Cognitive Load)	7, 8, 9	3,73	Height

Note: *ECL scores are calculated after reverse scoring on items 4, 5, and 6 (formula: 6 – original score).

Furthermore, to obtain a more concise picture of the level of cognitive burden in each aspect, an average calculation was made for each aspect as presented in Table 4. This calculation also takes into account the reverse scoring process on ECL items to make interpretation consistent, where higher scores indicate lower loads.

Table 6. Categorization and Interpretation of Extraneous Cognitive Load (ECL) Levels

Score Range	Category: ECL	3D Visualization Design Interpretation
1,00 – 1,80	Very Low	The design is very efficient; Visual and navigation elements do not place additional load on working memory.
1,81 – 2,60	Low	Efficient design; cognitive barriers from external elements are minimal and do not interfere with the learning process.

Score Range	Category: ECL	3D Visualization Design Interpretation
2,61 – 3,40	Medium	There are some design or navigation elements that are quite attention-grabbing beyond the core material.
3,41 – 4,20	Height	Design is less effective; Confusing visual elements begin to hinder information processing.
4,21 – 5,00	Very High	Design is ineffective; experience serious obstacles in understanding the material due to complicated instructions or visuals.

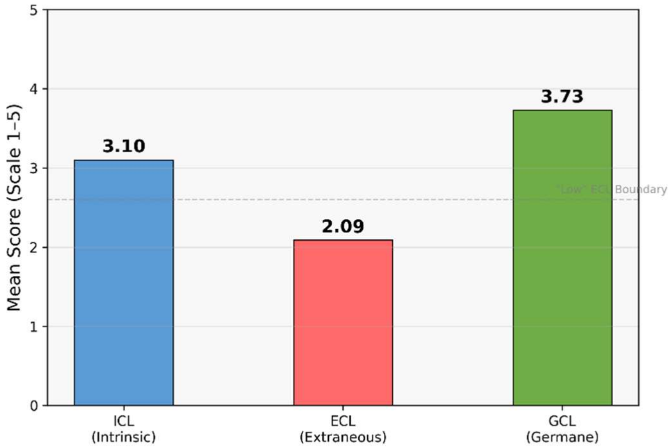

Figure 3. Comparison Chart of Average Aspects of Cognitive Load (ICL, ECL, GCL)

Based on Table 3 and Table 4 and Figure 3, the respondents' average ECL of 2.09 was in the low category (range 1.81–2.60). This indicates that the 3D visualization design in the developed e-module is relatively efficient and does not provide excessive extrinsic cognitive load on students' working memory. The average ICL of 3.10 (medium category) indicates that the complexity of the material is still within reasonable limits, while the GCL of 3.73 (high category) indicates the active involvement of students in constructing understanding through 3D visual media.

3.2. Learning Outcome Analysis

The analysis of learning outcomes was carried out on the pre-test and post-test scores of 48 students. The score is converted to a percentage scale (0–100) with a total of 15 items.

Table 7. Summary of Results of Analysis of Learning Outcomes Improvement

Analysis Aspect	Parameter	Pre-test	Post-test	Remarks
Statistics Descriptive	N	48	48	Number of respondents
	Average (%)	34,67	84,67	There was an increase of 50.00%
	Minimum (%)	13,33	40,00	-
	Maximum (%)	66,67	93,33	-
	Standard Deviation (%)	13,83	15,77	-
Normality Test (Shapiro-Wilk)	Statistics (W)	0,9457	0,6003	-
	Value p	0,1293	< 0.001	-
	Remarks	Normal	Abnormal	p > 0,05 = normal
Uji Hypothesis	Test Type	-	-	Wilcoxon Signed Rank Test
	Test Statistics (W)	-	1,000	-
	Significance Value (p)	-	0,000002	p < 0.05
	Slow Significance (α)	-	0,05	-
	Verdict	-	H_0 rejected	-
	Conclusion	-	significant improvement	After the use of the 3D e-module

Based on Table 6, the results of the analysis show that the average score of students has increased from 34.67% in the pre-test to 84.67% in the post-test, with a difference of 50.00%. This shows that there is a fairly high increase in learning outcomes after the use of e-modules based on 3D visualization.

The results of the normality test using Shapiro-Wilk showed that the pre-test data was normally distributed ($p > 0.05$), while the post-test data was not normally distributed ($p < 0.05$). Therefore, the analysis was continued using the non-parametric Wilcoxon Signed Rank Test.

Based on the results of the Wilcoxon test, a significance value of $p < 0.05$ was obtained, so that H_0 was rejected and H_1 was accepted. Thus, it can be concluded that the use of e-modules based on 3D visualization shows a significant increase in student learning outcomes.

3.3. Discussion: ECL Level and Design Implications

The results showed that the average ECL of students when using the e-module based on 3D Blender visualization was in the low category ($\bar{x} = 2.09$). These findings indicate that the interface design and 3D visual presentation applied to the e-module do not overload students' working memory. These results are in line with the basic principles of Cognitive Load Theory (CLT) which asserts that the effectiveness of learning depends on the ability of instructional design to minimize ECL so that cognitive capacity can be fully allocated to the formation of knowledge schemas (Zhu et al., 2026). The low ECL in this study can be attributed to several design decisions applied to e-modules. First, simplifying 3D visual elements through clean and not excessive rendering contributes to the cognitive efficiency of students. Li et al. (2025) states that the visual complexity of the interface positively correlates with an increase in the cognitive load of the user, so that a simple yet representative design is the key to the success of 3D media in learning. Second, intuitive e-module navigation also plays a role in suppressing ECL. (Zhu et al., 2026) It proves that the visual design features of the interface in digital media have a significant effect on the cognitive load of users, where a consistent and predictable layout significantly reduces irrelevant mental effort.

In contrast to immersive VR environments that risk increasing ECL and hindering learning outcomes, especially for beginners (De Witte et al., 2026; Sweller, 2024), the screen-based 3D visualization approach in this e-module provides adequate spatial representation without burdening learners with high interaction complexity. These findings also support the argument that simplifying visual elements and signaling are effective strategies in managing ECL in visualization-based media. The quality of interaction between users and media is proven to be able to suppress ECL and in turn improve learning outcomes (Yin & Sun, 2026).

On the other hand, a high GCL score indicates that learners are actively engaging in cognitive elaboration and relating 3D representations to their knowledge schemas. This is in line with the findings ($\bar{x} = 3{,}73$)Zhu et al. (2026) which suggests that a structured AR/MR approach can encourage productive cognitive engagement and improve learning performance. The combination of low ECL and high GCL is an ideal condition for 3D media-based learning, as argued by Tang et al. (2026) that the optimization of immersive learning requires a balance between minimizing extrinsic burdens and maximizing constructive cognitive processes.

3.4. Discussion: Learning Outcome Effectiveness

The results of the Wilcoxon Signed Rank Test showed a statistically significant improvement in students' learning outcomes after the implementation of the 3D Blender-based interactive e-module. The average score increased from 34.67% in the pre-test to 84.67% in the post-test, indicating an improvement of 50 percentage points. The significance value obtained was $p = 0.000002$, which is lower than the significance level of $\alpha = 0.05$. Therefore, H_0 was rejected, confirming that there was a significant improvement in students' learning outcomes after using the 3D e-module.

In addition to statistical significance, the magnitude of the improvement was also examined using normalized learning gain. The N-gain value was calculated based on the difference between the post-test and pre-test scores relative to the maximum possible score. Based on the average pre-test score of 34.67%, the average post-test score of 84.67%, and a maximum score of 100%, the obtained N-gain value was 0.765. This value falls into the high category, indicating that the 3D Blender-based interactive e-module produced a strong improvement in students' learning outcomes. Thus, the improvement of learning was not only statistically significant but also educationally meaningful.

The effect size of the Wilcoxon Signed Rank Test should also be reported to describe the practical strength of the intervention. The effect size can be calculated using the formula $r = Z/\sqrt{N}$, where Z is the standardized test statistic, and N is the number of valid paired observations. However, the available Wilcoxon output only reports the test statistic $W = 1.000$ and the significance value $p = 0.000002$, without providing the Z value and the number of valid paired observations. Therefore, the effect size cannot be calculated accurately from the available data. Once the Z value and N are obtained from the statistical output, the effect size can be reported further to support the interpretation of the e-module's practical effectiveness.

The results of the Wilcoxon Signed Rank Test showed a statistically significant improvement in learning outcomes, with the average score increasing from 34.67% to 84.67% or an increase of 50 percentage points. This substantial improvement indicates the effectiveness of interactive e-modules based on 3D Blender visualization as a learning medium. These findings are consistent with research ($p = 0{,}000002 < 0{,}05$) This is in line with the development of interactive e-modules can significantly improve students' understanding of concepts and thinking skills (Liunima et al. 2025).

The effectiveness of this e-module can be understood through 3D visualization's ability to concretize abstract representations of objects. Multidimensional visualization technology has comparative advantages in presenting spatial information that is difficult to represent through two-dimensional media (Han et al., 2025). In the context of learning 3D Blender material, students' ability to observe objects from various points of view and understand spatial relationships between components is greatly facilitated by this 3D-based e-module. This is in line with previous findings showing that the use of 3D scans in learning significantly improves learning outcomes compared to conventional 2D drawing media (Schirone et al., 2024).

Improved learning outcomes can also be attributed to the interactivity of e-modules that encourage active student engagement. Interactive web-based learning media has been found to significantly improve concept understanding and learning motivation (Abdamia et al., 2023). Furthermore, augmented reality technology in engineering education has been shown to improve learning outcomes through a more realistic and contextual learning experience (Suhail et al., 2024). The use of Blender 3D software in the development of e-modules allows for realistic and representative material presentation, which in turn facilitates a deeper understanding of concepts (Sari et al., 2022). The spatial aspect in design learning has also been shown to increase students' spatial sensitivity and representational abilities (El-Husseiny et al., 2025).

3.5. The Relationship of ECL and Learning Outcomes

Overall, the findings of this study illustrate a mutually supportive relationship between low ECL levels and significant improvements in learning outcomes. The design of the e-module, based on 3D Blender visualization that takes into account the principles of cognitive load management, has been proven to be able to create conducive learning conditions: minimal extrinsic cognitive load allows learners' working memory to be allocated more to the process of constructing meaningful knowledge (Zhu et al., 2026). This is empirically proven through high GCL and significant improvement in post-test scores. These findings reinforce the argument that the instructional design quality of 3D media, particularly in terms of visual simplicity, intuitive navigation, and precise signaling, is a crucial mediating variable between the use of 3D technology and learning effectiveness (Li et al., 2025).

4. CONCLUSION

This study concludes that the interactive e-module based on 3D Blender visualization has the potential to support effective learning by presenting complex and spatial material in a clearer and more accessible way. The low level of extraneous cognitive load experienced by students indicates that the design of the e-module, including its interface, navigation, text explanation, and 3D visualization, was able to reduce unnecessary mental effort during learning. This suggests that 3D-based learning media can be beneficial when it is designed with attention to cognitive load management principles.

The improvement in students' learning outcomes also shows that the e-module did not merely provide visual attractiveness but contributed meaningfully to students' conceptual understanding. By allowing students to observe objects more concretely and interactively, the 3D Blender-based e-module helped bridge abstract concepts with visual representation. Therefore, this learning medium can be considered a promising alternative for subjects that require spatial reasoning, object visualization, and conceptual comprehension.

The findings imply that the development of 3D learning media should not focus only on technological features, but also on how visual elements, navigation, and content structure support students' cognitive processes. However, this study is limited by the use of a one-group pretest-posttest design without a control group and by the involvement of participants from a single institution. Future studies are recommended to use a quasi-experimental design with a comparison group, involve broader participant characteristics, and examine additional factors such as motivation, self-efficacy, and learning engagement to provide a more comprehensive understanding of the effectiveness of 3D-based e-modules.

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