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Development and Implementation of AI-Driven Learning Media for Low-Power Inverter Mastery Using the ADDIE Model

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Abstract: Rapid technological advancements in electrical engineering education require innovative learning media that bridge the gap between theoretical concepts and practical applications, especially for complex topics such as low-power inverters. This study developed and evaluated an AI-integrated learning media for low-power inverters, utilizing the ADDIE (Analysis, Design, Development, Implementation, Evaluation) model. The media's effectiveness was assessed through a single-group pretest-posttest design involving 40 undergraduate electrical engineering students. Validation by content and media experts deemed the media highly feasible, with an average feasibility percentage exceeding 85%. The implementation results showed a significant improvement in students' cognitive competencies, with the average test score increasing from 59.75 (pretest) to 83.20 (posttest) and an N-Gain of 0.59, which is categorized as moderate. A paired-sample t-test confirmed a statistically significant difference ($p < 0.05$) between the pretest and posttest results. Furthermore, students' perceptions were very positive, especially regarding material understanding, learning motivation, interactivity, and self-directed learning. The novelty of these findings demonstrates that integrating artificial intelligence into learning media is not only technically and pedagogically feasible but also effective in improving the learning outcomes of electrical engineering students. The developed media has the potential for broader application in engineering education and supports continued innovation in smart technology-based learning environments.

Keywords: Artificial intelligence; ADDIE model; Electrical engineering education; Instructional media; Low-power inverter.

Introduction

The field of education, particularly in Electrical Engineering, continues to face significant challenges in adapting to the rapid advancement of technology (Al-Zahrani, 2024; Beke & Tick, 2024; Liu et al., 2025; Mann et al., 2021). The competencies of electrical engineering students are determined not only by their theoretical understanding but also by their ability to apply technical concepts in real-world situations (Chen et al., 2021; Murillo-Zamorano et al., 2019). One of the crucial components in the Electrical Engineering curriculum is the low-power inverter (Mathew & Naidu, 2024; Molina et al., 2019). These inverters have a wide range of applications, from renewable energy systems to electric vehicles; however, instructors often encounter difficulties in translating abstract theoretical concepts into practical, operational realities (Ariza & Olatunde-Aiyedun, 2023; Khan et al., 2022; Morey et al., 2024).

Although the integration of artificial intelligence (AI) in education is a rapidly developing field, there remains a scarcity of empirical research validating AI-based instructional media specifically designed for complex and abstract technical concepts, such as low-

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power inverters within the electrical engineering curriculum (Mustafa et al., 2024; Setiawan et al., 2025; Zhai et al., 2021). This study uniquely addresses this gap by developing and evaluating AI-based instructional media intended to enhance practical understanding of low-power inverter applications, employing the systematic ADDIE model to ensure pedagogical robustness (Almelhi, 2021; Luo et al., 2024; Shakeel et al., 2023; Spatioti et al., 2022). To overcome these challenges, the implementation of digital learning media has become an urgent necessity. (Hwang et al., 2020; Labadze et al., 2023; Strielkowski et al., 2025). Numerous studies indicate that digital media can enhance interaction between instructors and students, improve learning outcomes, and encourage students to innovate throughout the learning process (Serrano et al., 2023; Shoufan, 2020). One innovative approach in this context is the integration of artificial intelligence (AI) into instructional media (Vieriu & Petrea, 2025). AI enables the personalization of learning materials, provides instant feedback, and offers in-depth learning analytics based on real-time student data (Bhatia et al., 2024; Bhimavarapu, 2025; Shoaib et al., 2024).

The utilization of AI in instructional media for low-power inverters has the potential to fundamentally transform the learning approach, shifting it from a predominantly theoretical orientation to one that is more practical and interactive (Peftitsis & Mavroudi, 2022; Shahnia & Yengejeh, 2019). With AI-based instructional media, students can be more actively engaged through interactive simulations and adaptive feedback (López Gutiérrez et al., 2021). This approach facilitates a better understanding of complex concepts. It empowers students to apply them in real-world practice, thereby bridging the gap between theory and practice that is frequently encountered in engineering education (Kumar S et al., 2024).

Nevertheless, the integration of AI in engineering education is not without challenges, including limited technological infrastructure, inadequate access to high-quality data, and varying levels of instructor proficiency in utilizing these new technologies. Furthermore, ethical and privacy concerns have also become significant issues in the implementation of AI within educational environments. Given these potential benefits and challenges, this study aims to develop instructional media for low-power inverters integrated with artificial intelligence, utilizing the ADDIE (*Analysis, Design, Development, Implementation, Evaluation*) instructional development model. This research contributes to the paradigm of Engineering Education 4.0 by demonstrating how AI-integrated instructional tools can equip students with practical and analytical competencies essential for navigating an increasingly AI-driven electrical engineering landscape. The study is expected to contribute not only to the theoretical literature on instructional design but also to provide practical solutions for improving the competencies of electrical engineering students, particularly regarding their theoretical understanding and practical skills related to low-power inverters.

Method

This study employed a descriptive quantitative approach, using a one-group pretest-posttest design, to measure the effectiveness of AI-based low-power inverter instructional media. It is important to note that while this design is effective for assessing changes within a single group, it is inherently limited in establishing definitive causality due to potential threats to internal validity such as history, maturation, and testing effects. The development process for the instructional media followed the ADDIE instructional model, which consists of five main phases: Analysis, Design, Development, Implementation, and Evaluation. Each of these phases, as implemented in this study, is described below.

Analysis (Needs Analysis)

In this phase, a learning needs analysis was conducted to guide the development of instructional media. The researcher reviewed the Power Electronics course curriculum and the expected competencies, identifying gaps in students' understanding of low-power inverter concepts. The findings from the needs analysis emphasized the necessity for innovative instructional media integrated with AI to enhance interactivity and improve conceptual understanding. Additionally, this phase involved establishing learning objectives and formulating initial specifications for the media to be developed. This included preparing evaluation instruments, such as pretests and posttests, to assess students' baseline abilities and their progress after the intervention.

Design (Instrument and Media Design)

In the design phase, the instruments and components of the instructional media were developed. The primary data collection instruments were the pretest and posttest, which were administered to students to measure improvements in cognitive competence. The test items were constructed based on the indicators of the revised Bloom's Taxonomy, covering levels of ability from understanding to evaluation (Damayanti et al., 2020; Nkhoma et al., 2017). The tests consisted of a combination of multiple-choice and essay questions that reflected mastery of the concepts and applications of low-power inverters. The details of the indicators and the test formats are presented in Table 1.

Table 1. Framework of Pre-test and Post-test Instruments

Competency Indicators	Bloom's Taxonomy Level	Question Type	Question Number	Number of Questions
Identify the main components in a low-power inverter circuit	C1-Remembering	Multiple Choice	1, 2	2
Explain the working principle of SPWM	C2-Understanding	Multiple Choice	3, 4	2
Interpret the block diagram of an inverter`	C2-Understanding	Multiple Choice	5, 6	2
Calculate inverter efficiency	C3-Applying	Essay	7	1
Identify the effect of load on THD	C4-Analyzing	Multiple Choice	8, 9	2
Analyze inverter design errors	C4-Analyzing	Essay	10	1
Evaluate two designs based on output and efficiency	C5-Evaluating	Essay	11	1

Table 2. Framework of Content Expert Validation Instrument

Aspect Assessed	Assessment Indicators
Material Alignment	The material is consistent with the learning outcomes of the Power Electronics course.
Conceptual Accuracy	The material accurately covers the fundamental concepts and operating principles of low-power inverters.
Material Sufficiency	The material provides a balanced coverage of theoretical and applied aspects.
Clarity of Language	The language used is easily comprehensible to students.
Relevance to Questions	Pretest and posttest questions align with Bloom's Taxonomy indicators.

Table 3. Framework for Media Expert Validation Instrument

Aspect Assessed	Assessment Indicators
User Interface (UI) Design	The display is appealing, and the color scheme and layout are appropriate.
Navigation	Navigation between menus/media is user-friendly and not confusing.
Interactivity Quality	The media possesses effective interactive elements that support learning.
AI Integration	AI features (e.g., automatic feedback, recommendations) function properly.

Furthermore, an expert validation instrument was designed to assess the suitability of the learning content and media before they were implemented with students. Validation was conducted by six experts, comprising three content experts and three digital learning media experts. The assessment was conducted using a 5-point Likert scale questionnaire, which encompassed aspects such as content suitability, pedagogical coherence, visual presentation quality, and the integration of Artificial Intelligence (AI) features within the media. The Likert scale used consisted of five categories: 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, and 5 = Strongly Agree. The detailed aspects and indicators for content expert validation are presented in Table 2, and for media experts in Table 3.

Following the implementation of the learning media, student perceptions regarding their experience with the media were measured using a 5-point Likert scale questionnaire. The objective of this questionnaire was to ascertain the extent to which students responded to the learning media concerning material comprehension, feature interactivity, media display, and its influence on learning motivation and autonomy. The framework for the student perception questionnaire instrument is presented in Table 4.

Table 4. Framework for Student Perception Questionnaire Instrument

Indicator Assessed	Statement
Material Comprehension	This media assists me in comprehending low-power inverter concepts.
Learning Motivation	I feel more motivated to learn using this media.
Interactivity and Appeal	The interactive and AI features provide an engaging learning experience.
Learning Autonomy	I am able to learn independently with the aid of this media.

Development (Learning Media Development)

The development phase involved creating a low-power inverter learning media integrated with artificial intelligence. The objective of this development was to create media that fundamentally transforms the learning approach from a theoretical one to a more applied and interactive one, enabling students to engage actively through technical simulations and adaptive performance-based feedback.

The developed media takes the form of an AI-based interactive Simulation Module specifically designed to assist students in understanding the operating principles of low-power inverters. This module integrates Sinusoidal Pulse Width Modulation (SPWM) simulations, real-time visualization of AC waveform output, efficiency calculations, and Total Harmonic Distortion (THD) analysis. Students can adjust parameters such as load, switching frequency, voltage, and subsequently receive automatic feedback from the AI system, which provides suggestions for improvement if performance is not optimal.

Technically, this media was constructed using React.js for the interactive frontend interface and Python Flask for managing the simulation logic and artificial intelligence system on the backend. The AI component was developed based on a decision-tree classifier and a rule-based engine, enabling the media to adjust simulation scenarios based on previous user interactions (adaptive pathway).

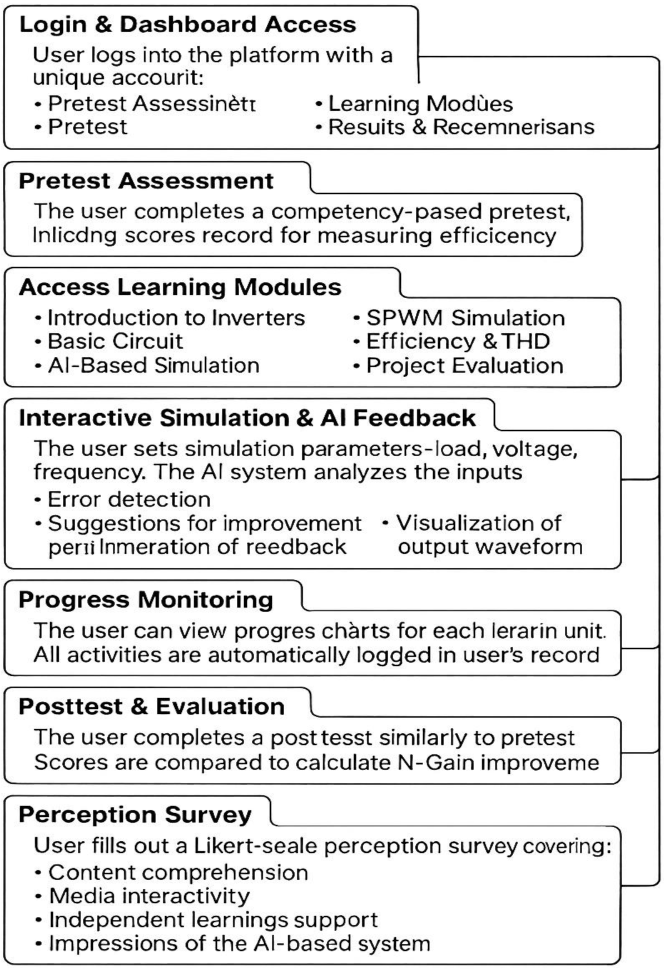


Figure 1. User Interaction Flow in AI-Based Inverter Learning Media

Figure 1 delineates the structured stages of student interaction with the learning media. Initially, users log in and access the dashboard, which presents options for the pretest, learning modules, and a review of results and recommendations. During the Pretest Assessment stage, students complete a competency-based pretest, the results of which serve as a baseline for measuring subsequent learning gains.

After the pretest, users proceed to the learning modules, which are organized into distinct units (e.g., inverter introduction, basic circuits, SPWM simulation, efficiency and THD, project evaluation). Within these modules, interactive simulations are integrated with AI-driven feedback. Students manipulate simulation parameters (such as load, voltage, and frequency). At the same time, the AI system analyzes these inputs to identify errors or provide corrective suggestions, concurrently presenting visualized outcomes (Interactive Simulation & AI Feedback stage).

Throughout the learning process, the system conducts continuous progress monitoring. Student progress and activities within each unit are automatically recorded, enabling visualization through progress graphs. Upon completing all modules, students undertake a post-test and evaluation that mirrors the initial pre-test. The posttest score is compared with the pretest score to calculate the N-Gain, indicating the extent of learning improvement. Finally, users complete a perception questionnaire designed to evaluate their learning experience, encompassing material comprehension, media interactivity, support for autonomous learning, and overall impressions of the AI-based system.

The architecture of this learning media system comprises several interconnected core components (Figure 2). The User Interface (frontend) functions as the primary student interaction module, providing access to the dashboard and learning modules. This interface communicates with the Application Server (backend), which manages users and modules, executes the pretest/posttest engine, and integrates the AI module for feedback analysis and data logging. All relevant data—including user profiles, module content, assessment results, learning progress, interaction logs, and survey responses—are stored in a centralized database.

Subsequent analysis and learning outcomes are managed by the Report Generator, which automatically produces comprehensive reports on student learning progress, including scores, N-Gain calculations, perception questionnaire results, and tailored recommendations. Additionally, a dedicated AI Engine supplies adaptive feedback, identifies errors, and performs advanced analyses of user performance.

This block diagram illustrates a layered system architecture: user interactions at the frontend are processed by the backend and AI engine, stored in the database, and ultimately returned to the user as detailed reports and instant feedback. This architecture enables AI-based learning media to function integratively and in real-time, thereby supporting a personalized and practical learning experience.

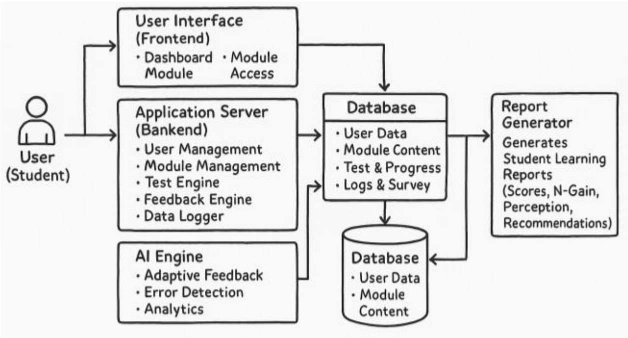


Figure 2. AI-Based Inverter Learning Media System Block Diagram

The development phase resulted in an AI-based interactive learning media, which is now ready for pilot testing. Figures 3 and 4 present the main user interface and the integrated content-simulation features designed within the media, respectively.

The main interface of the AI-based low-power inverter learning media is shown in Figure 3. The Simulation Area displays the inverter output voltage waveform (orange curve) alongside the PWM modulation signal (blue bars) in real time. The AI Feedback panel provides intelligent feedback or suggestions for improvement (e.g., "reduce switching frequency to lower THD"). The Performance Summary presents calculated values for Total Harmonic Distortion (THD) and system efficiency, accompanied by adjustable parameter settings (load, frequency, voltage) and controls to start or stop the simulation. All features are integrated within a single interactive interface, allowing users to modify parameters and immediately observe their effects on inverter performance.

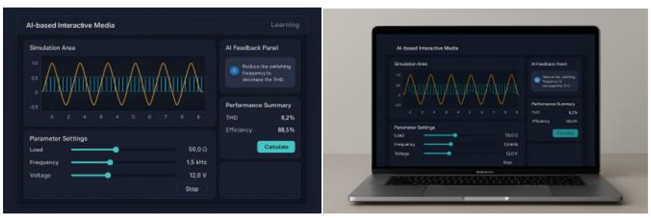


Figure 3. Low-Power Inverter Simulation Media Interface

This learning media integrates theoretical content with practical simulations within a single, unified module. The left panel (Figure 4) presents instructional material, including learning objectives, fundamental concepts of low-power inverters, the role of AI in learning, and practical experiment procedures. In contrast, the right panel provides an interactive simulation area for executing the low-power inverter model.

Students can review explanations and instructions while conducting simulation exercises simultaneously. This integration supports an adaptive learning flow, enabling users to apply the concepts they have acquired in practical simulations immediately. The AI panel offers automated feedback based on user actions, such as recommending a reduction in SPWM signal amplitude if high Total Harmonic Distortion (THD) is detected, thereby enhancing the personalization and contextual relevance of the learning experience.

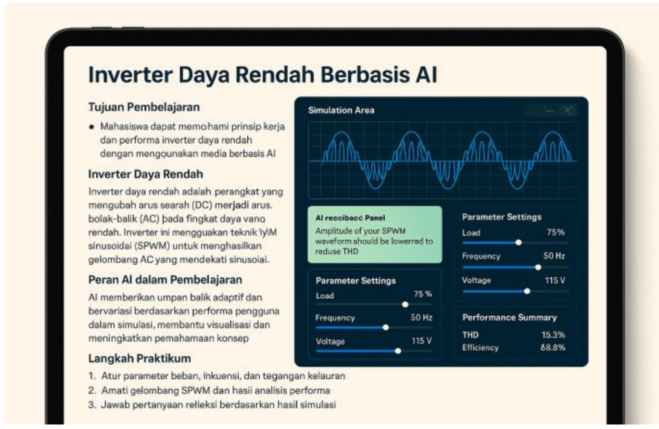


Figure 4. Integrated Learning Content and Interactive Simulation Display in the AI-Based Inverter Module

Upon completion of the media prototype development, validation was conducted by six expert validators, consisting of three subject matter experts and three media experts. The validation process assessed content validity, pedagogical coherence, and the technical quality of the user interface. The results of this validation informed subsequent revisions and refinements of the media prior to its full implementation in instructional activities.

Implementation (Media Implementation)

The developed and validated learning media were subsequently implemented with the research participants. This study employed a quantitative descriptive approach utilizing a one-group pretest-posttest design, in which measurements were conducted on a single group of students before and after the intervention, without a separate control or experimental group. The intervention involved 40 fourth-semester students from the Electrical Engineering Education Study Program, academic year 2024/2025, who were enrolled in the Power Electronics course.

During the implementation phase, a pretest was administered prior to the intervention, and a posttest was administered after the students had used the AI-based learning media for eight sessions, measuring improvements in cognitive competence. Validation data from six expert validators had been collected prior to student implementation. Following the intervention, a student perception questionnaire was distributed to assess their experiences regarding material comprehension, feature interactivity, media display, and the media's impact on learning motivation and autonomy. The research was conducted at the Electrical Engineering Education Study Program, Faculty of Engineering, State University, during the even semester, from February to April 2025.

Evaluation (Effectiveness and Feasibility)

Descriptive Analysis

Pretest and posttest data were analyzed using descriptive statistics to determine the mean, standard deviation, and score distribution of student performance. This analysis aimed to characterize students' cognitive competence both before and after the implementation of the learning media, establishing a baseline and measuring post-intervention outcomes.

Effectiveness Analysis via N-Gain

To assess the level of improvement in learning outcomes, the Normalized Gain Score (N-Gain) was calculated using the following formula (Prasetyo et al., 2018):

$$N - Gain = \frac{Posttest\ Score - Pretest\ Score}{100 - Pretest\ Score} \quad (1)$$

The calculated N-Gain values are categorized into three levels: high (≥0.7), medium (0.3–0.7), and low (<0.3), by Hake's (1998) criteria (Syahmani et al., 2022; Utami et al., 2024).

Inferential Analysis with Paired-Sample t-test

In addition to descriptive analysis, a paired-sample t-test was employed to determine the statistical significance of differences in learning outcomes (Ross & Willson, 2017). The procedure comprised the following steps:

a. Calculating the mean and standard deviation of pretest and posttest scores.
b. Computing the difference between posttest and pretest scores for each student.
c. Determining the calculated t-value, considering the score difference, standard deviation, and sample size.
d. Determining the degrees of freedom (*df*), which is n−1 (where n represents the number of research subjects).
e. Utilizing statistical software to process the data and obtain the significance value (p-value).

If $p<0.05$, a significant difference exists between the pretest and posttest scores, indicating the effectiveness of the learning media.

Expert Validation Analysis

Validation data from material experts and media experts were analyzed by calculating feasibility percentages based on the following formula (Ali & Rahayu, 2024):

$$Feasibility\ Percentage = \frac{Total\ Score}{Maximum\ Score} \times 100\% \quad (2)$$

Table 5. Criteria for Interpreting Media and Material Feasibility

Percentage Range (%)	Category
85-100	Highly Feasible
70-84	Feasible
55-69	Moderately Feasible
40-54	Less Feasible
< 40	Not Feasible

Result and Discussion

Descriptive Analysis of Pretest and Posttest Results

Descriptive analysis was performed to characterize the distribution and central tendency of Student learning outcomes before and after the use of the learning media. Data were collected from 40 fourth-semester students in the Electrical Engineering Education Study Program who completed both the pretest and posttest. Tables 6 and 7 present the frequency distributions of student pretest and posttest scores across various score intervals.

Figure 5 presents a histogram illustrating the distribution of student pretest scores prior to the learning media intervention. The majority of students scored within the 55–64 range, while several students scored below 45. These findings indicate considerable variation in baseline abilities and suggest that, on average, students had not yet fully comprehended the fundamental concepts of low-power inverters prior to the learning intervention.

Table 6. Distribution of Student Pretest Scores

Score Interval	Number of Students
40 – 44	3
45 – 49	5
50 – 54	7
55 – 59	9
60 – 64	9
65 – 69	3
70 – 75	4

Table 6 shows that prior to the use of the media, the majority of Students' pretest scores ranged from 55 to 64, although some students exhibited notably low initial scores (even below 45). This indicates a diversity of baseline abilities, with a general tendency toward the medium category. The wide range of pretest scores suggests varying levels of initial comprehension among students; while some demonstrated an adequate understanding of basic inverse concepts, many others had limited comprehension.

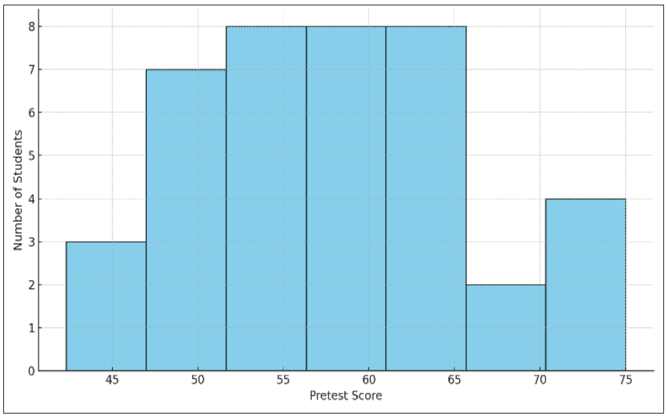


Figure 5. Distribution of Student Pretest Scores

Following the instruction with the AI-based media, student posttest scores were concentrated at higher values, as shown in Table 7. Most students achieved posttest scores of 80 or above, with some nearing the maximum score of 95. The score distribution shifted to the right compared to the pretest, indicating an overall improvement in performance. Only a few students scored below 75 after the intervention, signifying that the majority attained good competence in low-power inverter material.

Table 7. Distribution of Student Posttest Scores

Score Interval	Number of Students
70 – 74	2
75 – 79	7
80 – 84	12
85 – 89	12
90 – 95	5

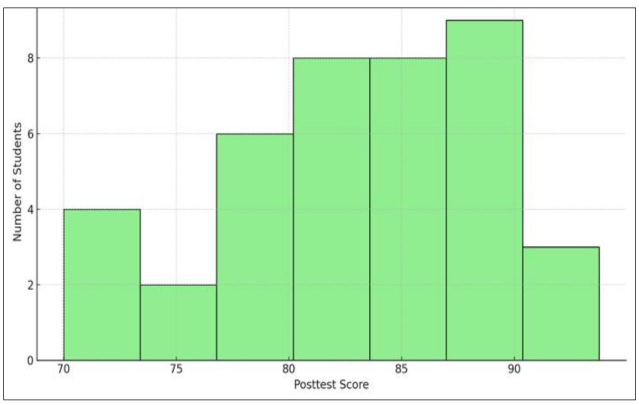


Figure 6. Distribution of Student Posttest Scores

Figure 6 presents a histogram illustrating the distribution of posttest scores after students used the AI-based learning media. Most students demonstrated improved performance, with the score distribution concentrated in the 80–89 range. This indicates that the majority of students achieved a high level of mastery following the learning intervention. Figure 7 presents a bar graph comparing the mean pretest score (59.75) and mean posttest score (83.20), confirming a substantial increase in student learning outcomes as a result of the intervention.

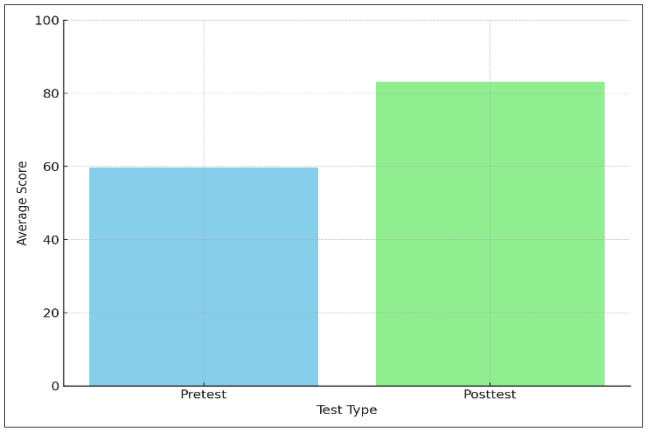


Figure 7. Comparison of Average Pretest and Posttest Scores

Table 8. Descriptive Statistics of Student Pretest and Posttest Scores

Statistic	Pretest	Posttest
N (Number of respondents)	40	40
Minimum Score	40.00	70.00
Maximum Score	75.00	95.00
Mean	59.75	83.20
Standard Deviation	8.90	6.70

To further examine the statistical trend of improvement, Table 8 presents the key descriptive statistics for student pretest and posttest results. As shown in Table 8, the mean pretest score was 59.75, indicating a moderate initial ability level, with a standard deviation of 8.90. This suggests that, prior to the intervention, students' comprehension levels were relatively dispersed.

Following the use of the developed learning media, the mean posttest score increased substantially to 83.20, accompanied by a decrease in standard deviation to 6.75. This reduction in score dispersion indicates that student learning outcomes became more uniform in the posttest—students who initially exhibited lower abilities improved, narrowing the gap with their higher-performing peers. The nearly 23.5-point increase in the mean score (from approximately 59.8 to 83.2) demonstrates a significant improvement in comprehension and material mastery as a result of the learning intervention with AI-based media.

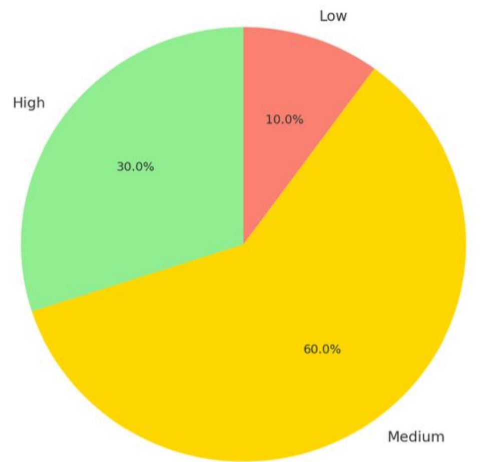
N-Gain Analysis

To assess the relative improvement in each student's learning outcomes, the Normalized Gain (N-Gain) was calculated using pretest and posttest scores. N-Gain serves as an indicator of learning effectiveness by measuring the difference between pretest and posttest scores relative to the maximum possible score (see Equation 1). N-Gain values were then classified according to standard criteria: high (N-Gain ≥ 0.7), medium (0.3–0.69), and low (< 0.3). The calculation results show that the mean N-Gain value for all students was 0.59, placing it within the medium category. This indicates a reasonably substantial proportional improvement relative to the potential for maximum achievement. The distribution of student N-Gain categories is presented in Table 9.

Table 9. Distribution of Student N-Gain Categories

N-Gain Category	Number of Students	Percentage
High	12	30%
Medium	24	60%
Low	4	10%
Total	40	100%

The majority of students (60%) demonstrated improvement within the medium category, while an additional 30% were classified in the high category. Only 10% of students exhibited low improvement according to the N-Gain metric (Figure 8). This distribution suggests that the developed learning media were generally effective in enhancing student comprehension of low-power inverter concepts. Most students significantly improved their scores, with more than a quarter approaching the maximum possible improvement. Notably, there were no students with an N-Gain of 0 (no improvement), indicating that all students benefited from the learning intervention, albeit to varying extents.



Gambar 8. Distribution of N-Gain Categories

Paired-Sample t-test

In addition to descriptive analysis, an inferential statistical test (paired-sample t-test) was conducted to determine whether the difference between pretest and posttest scores was statistically significant. The paired-sample t-test was chosen due to its appropriateness for comparing two measurements (before and after the intervention) from the same group of subjects. Prior to performing the test, basic assumptions—such as the normal distribution of score differences—were briefly examined using the previously presented descriptive statistics.

The results of the paired-sample t-test are shown in Table 10. This test compared the mean pretest and posttest scores from a sample of 40 students, with the null hypothesis indicating that there is no significant difference in means before and after the use of the media.

Table 10. Results of Paired-Sample t-test for Pretest and Posttest Scores

Variable	t-value	df	Sig. (2-tailed)
Pretest vs Posttest	-14.723	39	0.000

Table 10 shows that the Sig. (2-tailed) The value is 0.000, which is below the significance threshold of 0.05. Therefore, the t-test results indicate a statistically significant difference between student pretest and posttest scores. A t-value of -14.723 with 39 degrees of freedom (df) demonstrates that the posttest mean is substantially higher than the pretest mean (the negative sign reflects the calculation of posttest minus pretest). This finding leads to the rejection of the null hypothesis, confirming that the use of AI-based learning media had a significant effect on enhancing students' cognitive competence. In practical terms, learning with this new media successfully and significantly improved student learning outcomes, corroborating the previously observed increases in mean scores and N-Gain.

Expert Validation

Validation analysis was conducted to determine the feasibility level of the developed learning media prior to its implementation with students. Two groups of experts conducted validation, comprising three subject matter experts and three media experts, using a 5-point Likert scale questionnaire that assessed aspects of content, design, and technical features of the learning media. Each validator's assessment was converted into a feasibility percentage score using Equation 2.

The summarized results of the expert assessments are presented in Table 11. Each validator assigned scores across five main aspects, with a total maximum score of 25 (5 aspects × a maximum value of 5). The feasibility percentage was calculated by comparing the obtained score to the maximum possible score.

Table 11. Expert Validation Results for Material and Media Experts

Validator	Maximum Score	Obtained Score	Percentage (%)	Category
Material Expert 1	25	23	92.00	Highly Feasible
Material Expert 2	25	22	88.00	Highly Feasible
Material Expert 3	25	23	92.00	Highly Feasible
Average Material Expert	25	22.67	90.67	Highly Feasible
Media Expert 1	25	21	84.00	Feasible
Media Expert 2	25	22	88,00	Highly Feasible
Media Expert 3	25	21	84.00	Feasible
Average Media Expert	25	21.33	85.33	Highly Feasible

Based on Table 11, the average feasibility percentage assigned by the material experts was 90.67%, categorizing the media as Highly Feasible. The media experts provided an average feasibility percentage of 85.33%, which also falls within the Highly Feasible category. Although two of the three media experts assigned scores of 84% (categorized as Feasible), one expert assigned 88%, thereby elevating the overall average above 85%. These findings indicate that the developed AI-based learning media meets feasibility standards in terms of both content and design/technical aspects. The content was rated as highly aligned with learning outcomes and conceptually accurate, while the media aspect was noted for its appealing display, user-friendly navigation, and functional AI interactivity. In summary, the experts agreed that the media is suitable for instructional use without the need for significant revisions. This validation outcome provides confidence that the media can be widely implemented to support low-power inverter instruction in real classroom environments.

Figure 9 presents a graph illustrating the validation results from both material and media experts. The average feasibility percentage exceeded 85%, placing it within the "Highly Feasible" category. This indicates that the developed learning media have satisfied feasibility standards in terms of both content and design aspects.

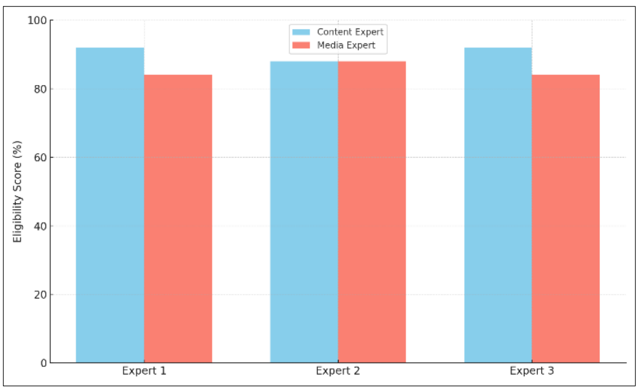


Figure 9. Validation Results by Expert Type

Student Perceptions

Following the use of the media in the learning process, student perceptions were assessed to gather end-user feedback. Students were asked to complete a 5-point Likert scale perception questionnaire addressing several indicators, including the media's effectiveness in aiding material comprehension, its impact on learning motivation, the degree of interactivity and appeal, and its support for autonomous learning. Table 12 presents the mean student perception scores for these four primary indicators.

The results presented in Table 12 indicate that student perceptions of this learning media are highly positive across all assessed aspects. All indicators received a mean score above 4.0 (on a maximum scale of 5), corresponding to the categories of "Agree" to "Strongly Agree."

The "Interactivity and Appeal" indicator received the highest score (4.5), signifying that students perceived the AI-based media as highly interactive and engaging, which enhanced their involvement in the learning process. The "Material Comprehension" indicator was also rated highly (4.4), indicating that students recognized the media's effectiveness in facilitating their understanding of low-power inverter concepts. The "Learning Motivation" aspect (4.3) reflects an increased impetus for learning when using the media, likely attributable to a more active and visually engaging approach compared to traditional methods. Finally, the "Autonomous Learning" score (4.2) suggests that the media supports independent study, with students feeling capable of managing their own learning pace and direction through AI features such as instant feedback and adaptive material adjustments.

Table 12. Mean Student Perception Scores Toward the Media

Perception Indicator	Average Score (1-5)
Understanding of Material	4.4
Learning Motivation	4.3
Interactivity and Engagement	4.5
Independent Learning	4.2

Overall, these user responses demonstrate a high level of satisfaction and acceptance of the innovative learning media, reinforcing the conclusion that AI integration in electrical engineering education can significantly enhance student comprehension, motivation, interactivity, and autonomous learning.

Figure 10 presents a graph illustrating the mean student perception scores for the AI-based learning media across four primary indicators: material comprehension, learning motivation, interactivity, and autonomous learning. All indicators received scores above 4.0 (on a 1–5 scale), demonstrating a very high level of student acceptance and satisfaction.

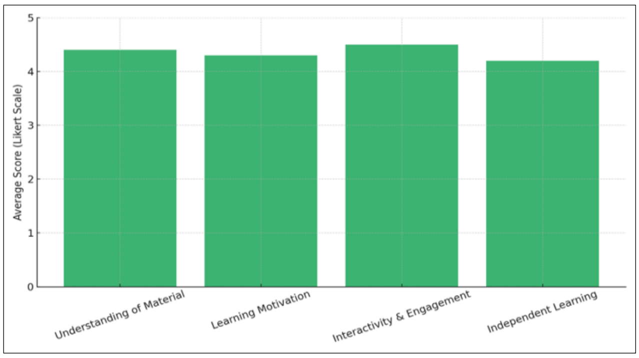


Figure 10. Average Student Perception Scores on AI-Based Learning Media

Conclusion

This study successfully developed and implemented a low-power inverter learning media integrated with Artificial Intelligence (AI), utilizing the ADDIE instructional model. Expert validation results indicated that the developed media is highly feasible for instructional use, with average feasibility percentages exceeding 85%. Implementation with electrical engineering students resulted in a significant improvement in cognitive competence, as evidenced by the increase in mean scores from pretest to posttest and an N-Gain value of 0.59, classified as medium. A paired-sample t-test further confirmed a statistically significant difference between the pretest and posttest results ($p < 0.05$). Moreover, student perceptions of the media were overwhelmingly positive, particularly in terms of material comprehension, learning motivation, interactivity, and autonomous learning. These findings confirm that integrating AI into electrical engineering learning media is not only technically and pedagogically feasible but also effective in enhancing student learning outcomes. The developed learning media also hold promise for adaptation to other specialized fields and support continued innovation in innovative technology-based education within higher technical education environments.

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Author Contributions

Conceptualization, S.P. and B.D.W; methodology, B.D.W; software, W.P.; validation, S.P., B.D.W, and S.A.B.Z.; formal analysis, B.D.W.; investigation, B.D.W; resources, S.P.; data curation, B.D.W; writing—original draft preparation, B.D.W.; writing—review and editing, S.P. and S.A.B.Z.; visualization, W.P.; supervision, S.P.; project administration, S.P.; funding acquisition, S.P.. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare no conflict of interest.

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