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# The Role of Adaptive Learning in the Training of Electronics and Automation Engineers

**Kristina Ivanchenko**

*Project manager (Škoda Enyaq), Kromberg and Schubert Ukraine, Zhytomyr, Ukraine, https://orcid.org/0009-0005-2173-7874*

***Correspondence email:** *kristina_ivanchenko@outlook.com.*

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**Abstract:** The rapid advancement of Industry 4.0 and 5.0 necessitates a transformation in engineering education, particularly in electronics and automation. Conventional approaches to instruction do not meet the different needs of learners, which contributes to skill deficiencies within the workforce. This research analyzes the impact of adaptive learning on academic achievement, problem-solving abilities, and engagement relative to other traditional methods. A quasi-experimental design was utilized for 124 engineering students separated into two groups: an experimental group receiving AI-based adaptive learning and a control group taught with lectures followed by manual drills. Quantitative information was retrieved through pre and post-tests, while qualitative data was acquired through surveys and teacher observations. The findings showed that the adaptive learning portion significantly outperformed the other group in later CG scores (33.3% vs 12.0%, $p < 0.001$, Cohen's d = 1.26) and student participation (84.7% vs 62.3%). Main engagement drivers were identified as personalized learning paths, immediate feedback, and slack in the learning pacing. Other noted limitations included the lack of technological infrastructure and difficulties in initial adaptation. These results offer evidence that adaptive learning can narrow the gap between engineering education and industry requirements and recommend incorporating its use into higher education programs as a blended learning and stronger AI-cantered projects. Further studies ought to look into the effects of adaptive learning on workforce preparedness over time, personalized learning strategies, and large-scale implementation across all engineering fields.

**Keywords:** adaptive learning, engineering education, AI-driven learning, problem-solving skills, student engagement, Industry 4.0, automation training.

## Introduction

The advancement of technology and industrial activities has transformed higher education, especially in engineering. The automation revolution - 4.0, which revolves around intelligent automation, IoT, and Artificial Intelligence, has changed the skill requirements. Industry 5.0 has added more complexity to the challenges facing higher education by putting more focus on the interaction between humans and technology. There is a consensus among instructors and practitioners that there is an urgent need for a paradigm shift in teaching engineering. As Singh (2016) and Mulenga & Marbán (2020) discuss, increased attention should be given to digital learning and the broader digitalization of education. However, due to their passive and conventional nature, traditional teaching systems are often unable to meet the fast-changing, technology-driven demands of modern industries. This underscores the need for new instructional models that are more flexible, active, and data-driven, especially in rapidly evolving fields such as mathematics, electronics, and automation.

To meet these challenges, adaptive learning has developed as a new phenomenon in higher education. Adaptive learning is a technique where instruction is done through a computer using artificial intelligence and data mining to match the student's content requirements. Studies show that the cognitive developments of students are significantly impacted positively by AI-based adaptive learning systems (Haldorai et al., 2021). This method provides learners with responsive and personalized education where content and pedagogical approaches are automatically altered based on the learner's understanding and the rate of learning. In the field of electrical and automation engineering, (Abdul Majid & Fuada, 2020) introduced a learner-centred model that aligns with the principles of Industry 4.0 to enhance the quality and inclusivity of education. In the context of electronics and automation, the demand for engineers who are capable of adapting to ongoing technological changes continues to grow, highlighting the importance of integrating such adaptive models into instructional design. Today's industry requires graduates with not only theoretical knowledge but also critical, analytical thinking and problem-solving skills in high-tech settings (Zhao et al., 2019). However, traditional learning systems often fail to keep pace with the rapid evolution of industry. Adaptive learning presents a multifaceted educational approach that leverages advanced technologies such as AI and big data to personalize learning experiences according to individual student needs, thereby enhancing deep understanding and real-world application (Roll & Wylie, 2016). In response, the education system has begun to implement smart education frameworks that combine adaptive learning, robotics, and AI devices, which, of course, make the process of implementing education more relevant in the Industry 5.0 era (Hassan et al., 2021). This innovation aims to drive transformative changes in the future workforce. However, challenges to the implementation of AI still exist, especially regarding the ethics of using AI (Saghafian et al., 2021). In this context, several studies, especially those focusing on engineering education, have prioritized problem-solving skills, academic performance analysis, and student engagement levels through adaptive learning strategies compared to traditional methods (Clark & Kaw, 2019) indeed.

The continued reliance on traditional approaches in engineering pedagogy presents significant challenges, particularly in addressing the diverse and complex needs of learners. Conventional learning systems often exhibit rigidity by expecting uniform performance from all students, disregarding individual differences in learning styles, comprehension speed, and cognitive abilities. Such methods tend to emphasize passive absorption and rote memorization of content, which proves ineffective in preparing students to meet the dynamic demands of the industrial world. Research indicates that high failure rates in engineering courses, such as Engineering Dynamics, are partly due to structural barriers inherent in rigid, systematic teaching models (Makki et al., 2016). Also, the absence of consistent and structured instructional strategies often hinders students' ability to transfer theoretical knowledge into practical applications, thereby widening the gap between formal education and industry expectations (Fan & Yu, 2017). Therefore, the need to integrate technology into engineering education becomes increasingly urgent as the limitations of traditional methods fail to meet the evolving requirements of modern learners (Singh et al., 2016).

Adaptive learning technology has shown promising results in improving learning outcomes for engineering students compared to traditional instructional methods. Multiple studies have found that adaptive learning systems lead to better exam performance and concept understanding (Clark & Kaw, 2019; Cui et al., 2018). These systems provide personalized learning pathways, just-in-time feedback, and tailored content based on individual student needs (Barclay et al., 2020; Panicker et al., 2018). When combined with flipped classroom approaches, adaptive learning has demonstrated particular effectiveness, especially in online environments (Clark & Kaw, 2019). Benefits include improved classroom perceptions, increased motivation, and reduced stress for students. However, some research suggests that adaptive learning may be more efficient than effective, with traditional methods potentially yielding similar outcomes (White, 2020). Overall, adaptive learning shows potential for enhancing engineering education, though further research is needed to fully understand its impact across different contexts.

Adaptive learning accommodates the shortcomings of the traditional method in both academic and pedagogical views. Unlike rigid, one-size-fits-all methods, adaptive content is modified based on student feedback and interaction, fulfilling the engineering requirement of understanding and solving a problem deeply. This research analyzes the impact of adaptive learning on problem-solving abilities, academic performance, student engagement in engineering education, and its potential to improve graduates' preparedness for sophisticated industrial demands.

Numerous studies across different fields have confirmed the effectiveness of adaptive learning systems in fostering academic achievement, engagement, and personalized learning experiences (Troussas et al., 2021). Unfortunately, there is little to no literature regarding its application in engineering education, more so in electronics and automation. This study aids in bridging the gap by analyzing the impact of adaptive learning on problem-solving and students' employment readiness, two critical aspects that have not been studied extensively in this regard. Also, this research provides one more contribution by integrating adaptive learning with engineering education problems related to Industry 4.0 and 5.0, thus creating a base for developing more flexible, innovative, and technologies-based curricula.

This study seeks to examine how effective adaptive learning is in improving the learning experience of students who are studying for a degree in electrical and automation engineering. More specifically, it assesses changes in academic achievement, problem-solving, and participation in class activities. With the use of AI-driven content customization, adaptive learning is presumed to provide flexibility and responsiveness compared to conventional techniques.

In order to achieve this goal, it addresses three key *research questions:*

1. How does adaptive learning affect the academic performance of engineering students compared to traditional learning methods?

2. What are the primary benefits and challenges encountered in implementing adaptive learning in engineering education?
3. How do students perceive the effectiveness of adaptive learning in electrical and automation engineering education?

Answering these questions will help derive factors influencing the strength and boundaries of adaptive learning in engineering education with a practical lens. In order to test the efficacy of this approach, the study presents the following *hypotheses*:

- $H_0$ (Null hypothesis): There is no significant difference in academic performance and problem-solving skills between students who undergo adaptive learning training and those who engage in traditional learning.
- $H_1$ (Alternative hypothesis): Students who undergo adaptive learning training demonstrate higher academic performance and problem-solving skills than those who learn in a traditional learning environment.

This research attempts to prove how adaptive learning can improve engineering education and analyze its application for the electrical and automation engineering program in the present day by validating these hypotheses.

## Literature Review

### *Definition of Adaptive Learning*

Artificial Intelligence (AI)-based adaptive learning is an innovative pedagogical approach that seeks to customize educational experiences to meet individual student needs. This learning model leverages advanced technologies like AI to deliver personalized instructional strategies to improve learning outcomes. The application of AI in adaptive learning is particularly relevant in Industry 4.0, characterized by rapid technological advancements that necessitate adaptable educational frameworks (Peng et al., 2019). Integrating web-based adaptive systems allows real-time monitoring of students' learning habits and performances, enabling educators to dynamically adjust teaching methodologies and resources according to learners' evolving needs. This flexibility is crucial for equipping students with competencies that align with labour market demands in an increasingly technology-driven era (Elmabaredy et al., 2020; Sánchez Ruiz et al., 2021).

The transformation of adaptive learning in higher education reflects a broader push toward integrating innovative technologies that enhance the learning experience. During the COVID-19 pandemic, many institutions hastily transitioned to online learning environments, revealing both the potential and challenges of effectively using adaptive methodologies. Studies have indicated that while the initial implementation of adaptive learning systems was limited, demand surged for personalized education strategies in response to evolving educational needs (Mirata et al., 2020; Dimauro et al., 2019). Furthermore, blending traditional learning with modern technologies has empowered educators to facilitate critical thinking and deep learning through resources tailored to individual student profiles (Sánchez Ruiz et al., 2021; Utami et al., 2021). The relevance of adaptive learning in the context of the Fourth Industrial Revolution is increasingly evident, as educational frameworks must transform to prepare students for future workplaces characterized by automation and intelligent systems (Guerrero-Roldán et al., 2021). Personalized learning enriches academic experience and enhances students' abilities to adapt to a rapidly changing job market, aligning education more closely with industrial demands.

### *Related Studies on Adaptive Learning in Engineering*

A new study proposes that adaptive learning can aid learning in Electronics and Automation in Electrical Engineering, Mechatronics, and Automation. In adaptive learning systems, interactive simulations, AI-driven evaluations, and active material transfer improve the learning experience of engineering students. Adaptive learning in engineering education has gained significant attention in recent years, offering personalized learning experiences tailored to individual student needs (Barclay et al., 2020; Panicker et al., 2018). Studies have shown that adaptive learning systems can improve student mastery of engineering concepts, particularly in computer engineering and mathematics (El-Sabagh, 2021; Clark & Kaw, 2020). These systems employ various strategies, such as adaptive feedback and navigation, often based on learning styles (Kerby et al., 2021). Research in this field has focused on designing, developing, implementing, and evaluating adaptive learning environments (Schunk, 2012; Clark & Kaw, 2020). While adaptive learning has demonstrated potential benefits in engineering education, including improved student engagement and performance, more research is needed to fully understand its impact and optimize its implementation across different engineering disciplines (Panicker et al., 2018). Applying interactive simulations, AI-powered assessment, and flexible content delivery has transformed engineering education. Such a system fosters a deep understanding of concepts, mastery of technical skills, and readiness for contemporary industry issues through adaptive learning in Electrical Engineering, Mechatronics, and Automation degree programs.

### *Comparison of Characteristics with Traditional Learning Methods*

In engineering education, conventional learning modes still heavily depend on lectures and manual practice, which are largely non-personalized. As a result, traditional approaches often struggle to accommodate students' diverse learning paces, leading to suboptimal mastery of engineering skills (Metsäpelto et al., 2022). Additionally, these methods emphasize passive memorization overactive inquiry, which can limit student engagement and diminish learning motivation (Ruiz et al., 2021). The lack of flexibility and interactivity also weakens the effectiveness of engineering education, where hands-on experimentation and problem-solving are essential. Moreover, research has indicated that in fields such as electrical and automation engineering, students frequently encounter challenges applying theoretical knowledge to real-world situations, further widening the gap between academic instruction and industrial requirements (Mahapatra, 2020).

To address these limitations, adaptive learning leverages technological solutions that provide personalized feedback, promote active engagement and support students' learning progress at their own pace. Unlike traditional models, AI-enhanced adaptive learning systems dynamically adjust instructional pathways based on student's performance data and learning behaviour (Chen et al., 2010). This adaptive mechanism empowers learners to interact with content that aligns with their understanding, encourages deeper learning, and prepares them more effectively for the demands of modern engineering industries. Students are effectively positioned to respond to contemporary industry challenges through this form of information-based customization.

### *Technological Tools in Adaptive Learning*

Artificial intelligence (AI), when integrated with learning analytics, plays a crucial role in automating the personalization of study programs based on individual learners' behaviours and performance. AI-based adaptive learning systems are considered to provide flexible, responsive, and data-driven educational experiences that adjust instruction to meet student needs (Cui et al., 2018). In the context of engineering education, platforms such as Smart Sparrow and Coursera have pioneered adaptive learning models by dynamically adjusting learning materials based on ongoing assessment results (Chaisongkram, 2020). These systems have been shown to enhance student engagement and improve technical skill acquisition through intelligent content delivery and feedback mechanisms.

In addition, interactive simulations and virtual laboratories have become essential tools for adaptive learning in fields like automation and electrical engineering. Engaging in computer-based experiments enables students to participate actively, fosters self-directed learning, and strengthens technical proficiency (Aşık et al., 2019). Research has shown that virtual labs contribute to improved conceptual understanding, greater confidence, and enhanced academic outcomes, particularly when used as part of a personalized, adaptive learning environment (Kapilan et al., 2021; Radhamani et al., 2021). The integration of such simulations within AI-supported frameworks allows for responsive, student-centred learning experiences that not only improve engagement but also better align with industry competencies.

***Theoretical Framework***

According to constructivist theory, as developed by Piaget and Vygotsky, learning is an active and dynamic process through which individuals construct knowledge by interacting with their environment (Kim et al., 2021). This theory aligns well with adaptive learning principles, which emphasizes personalized learning experiences driven by student engagement. Adaptive learning leverages technology to scaffold complex tasks and introduce new information progressively, supporting deeper cognitive engagement (Ifenthaler, 2012). This translates to interactive simulations, adaptive assessments, and AI-driven content matching the learner's cognitive level. Within environments such as game-based learning and technical simulations, adaptive scaffolding based on interaction data has optimised cognitive load and performance (El Kharki et al., 2021). This enables students to practice experiential learning that supports critical thinking and effective problem-solving.

Self-regulated learning (SRL) theory also reinforces the foundation of adaptive learning. Students perform better when they can monitor, adjust, and control their learning processes (El-Sabagh, 2021). In real-time adaptive environments, systems dynamically adjust the level of challenge and support based on student behaviour, facilitating cognitive alignment and deeper understanding (Isa & Azid, 2021). These adjustments help learners develop strategies to navigate new information and align comprehension with performance. Constructivist and self-regulated learning theories form a strong theoretical base for adaptive learning, supporting increased learner autonomy, personalized experiences, and greater alignment between educational design and learner needs. Automated, AI-driven systems have also demonstrated advantages over traditional lecture-based instruction, particularly when exercise types and learning domains are adapted to what students already understand.

Despite its potential, adaptive learning remains underexplored in engineering education, especially in training electronic and automation engineers. There is limited quantitative evidence comparing adaptive learning with traditional instructional methods in this domain (Yudiono et al., 2019). Furthermore, there is a lack of clarity regarding how adaptive systems influence the development of industry-relevant skills and graduate readiness in the context of Industry 4.0 and 5.0 (Suarez-Fernandez de Miranda et al., 2021). While existing literature confirms that AI-based adaptive learning systems can improve learner motivation and engagement, little is known about how such systems can be effectively integrated into automation and electrical engineering teaching frameworks. Therefore, this study aims to bridge this gap by conducting a comprehensive analysis of academic performance, motivation, participation, and industry preparedness. The results will inform future curriculum design by integrating adaptive learning technologies to improve instructional relevance and alignment with evolving industrial demands.

## Materials and Method

This research utilizes a quasi-experimental approach; this approach aims to assess the impact of adaptive learning in electrical and automation engineering education. This method makes measuring the difference between adaptive and traditional learning techniques possible without interfering with existing educational systems. Although lacking full control of the environment, both results and scientific rigour are preserved when employing a quasi-experimental design. This flexibility leads to greater accuracy in evaluating causation, which enhances the usefulness of the study's findings, particularly in designing technology-enhanced curricula for engineering education.

### *Sample and Research Procedure*

The experimental group learned through an AI adaptive learning system, while the control group continued with the traditional learning methods. The study participants were three to four-year university students listed in a course under Electrical Engineering, Automation, and Mechatronics. They knew basic arithmetic and programming, showcasing passing grades. Purposive sampling was employed as guided by the study's objectives to collect participants who met satisfactory educational qualifications relevant to the study (Chao et al., 2017). This choice of technique ensures that the study focuses on the impact of adaptive learning on engineering students' skills and knowledge.

This study was conducted in several sessions consisting of a baseline assessment, adaptive learning intervention, and a follow-up assessment designed to measure the degree of achievement alignment with the goals of enhancing students' academic attainment, problem-solving skills, and participation. This method enables a more precise granular breakdown of the data, which reveals the gaps in student success metrics whereby more adaptive learning techniques are employed against traditional methods.

### *Instrument and Data Collection Technique*

This research uses multi-method descriptive approaches involving quantitative and qualitative analyses in assessing the effectiveness of adaptive learning (Shannon-Baker, 2016). The quantitative technique includes measuring two-tailed t-test results for the pre-test and post-test scores of the experimental and control groups, in addition to ANOVA for the intervening variables in learning adaptation. The qualitative method implemented an interview and survey based on a thematic analysis of motivation, engagement and challenges in adaptive learning (Chenail, 2015). All these methods provide a better understanding of the effects of adaptive and traditional learning methods.

**Table 1**

*Data Collection Grid*

| Data Type | Collection Methods | Objectives | Instruments |
|---|---|---|---|
| Quantitative | Academic test (Pre-test and Post-test) | To measure the increase in student understanding before and after the intervention. | Exam questions based on electronic concepts & automation. |
| | Adaptive quiz & assignment completion rate | To assess student engagement in the adaptive learning system. | Adaptive learning system data (processing time, success rate, and interaction with the platform). |
| Qualitative | Survey & interview | To explore student perceptions of the learning experience with adaptive learning. | Questionnaires and semi-structured interviews. |

| | | | |
|---|---|---|---|
| | Instructor observation | To assess interaction patterns, class participation, and differences in engagement between groups. | Observation sheets based on engagement indicators. |

*Source:* author's development

***Data Analysis***

This research uses multi-method descriptive approaches involving quantitative and qualitative analyses in assessing the effectiveness of adaptive learning (Shannon-Baker, 2016). The quantitative technique includes measuring two-tailed t-test results for the pre-test and post-test scores of the experimental and control groups, in addition to ANOVA for the intervening variables in learning adaptation. The qualitative method implemented an interview and survey based on a thematic analysis of motivation, engagement and challenges in adaptive learning (Chenail, 2015). All these methods provide a better understanding of the effects of adaptive and traditional learning methods.

***Reliability and Validity Considerations***

To ensure the accuracy and consistency of the research instruments, validity testing was conducted through expert review, while reliability testing was performed using internal consistency analysis. The data was also triangulated by combining quantitative and qualitative methods to enhance the credibility of the research findings (Chenail, 2015). The pre-test and post-test were validated using Pearson Product Moment correlation, and their reliability was assessed with Cronbach's Alpha to ensure a high level of instrument reliability.

**Table 2**

*Results of Instrument Validity and Reliability Tests*

| Instruments | Validity Test (Pearson Correlation, r) | Validity Criteria | Reliability Test (Cronbach's Alpha, α) | Reliability Criteria |
|---|---|---|---|---|
| Pre-test | 0.78 | Valid | 0.85 | Reliable |
| Post-test | 0.82 | Valid | 0.88 | Reliable |
| Motivation Survey | 0.75 | Valid | 0.83 | Reliable |
| Interview | Data triangulation (convergence of survey results & observations) | Valid | 0.81 | Reliable |

*Source:* author's development

***Ethical Considerations***

This study ensures compliance with ethical standards through three main aspects: informed consent, confidentiality, and bias reduction. All participants provided written informed consent and were informed about the study's purpose and procedures, as well as their right to withdraw at any time. And even make sure that private data can be kept private, preventing the use of the data in any manner outside the academic use while keeping it in a safe place where no one but selected individuals can access it. The study features standardized evaluation instruments, balanced task distribution, and objective data analysis to reduce bias and improve the findings' validity and reliability.

## Results

This investigation comprised 124 students from the different Electrical Engineering, Mechatronics, and Automation branches. They were equally divided into 62 students in the experimental group, which applied adaptive learning, and 62 in the control group, which utilized traditional methods. Most students were male (76.6%), and women were 23.4%. Regarding degree programs, 44.4% were for Electrical Engineering, 31.5% for Mechatronics, and 24.2% for Automation. The sample comprised 50.8% of students in the third year and 49.2% in the fourth year. Most of them were aged 21-22 years (57.3%). A preliminary questionnaire revealed that 85.5% of the respondents had no experience with adaptive learning, 12.1% had some, and 2.4% had moderate. The balanced demographics contributed to the study's internal validity by minimizing external variables. Demographic details are summarized in Table 3.

**Tabel 3**

*Demographic Data of Participants*

| Demographic Characteristics | Experimental Group (n=62) | Control Group (n=62) | Total (n=124) |
|---|---|---|---|
| Gender | | | |
| Male | 48 (77.4%) | 47 (75.8%) | 95 (76.6%) |
| Female | 14 (22.6%) | 15 (24.2%) | 29 (23.4%) |
| Study Program | | | |
| Electrical Engineering | 28 (45.2%) | 27 (43.5%) | 55 (44.4%) |
| Mechatronics | 19 (30.6%) | 20 (32.3%) | 39 (31.5%) |
| Automation | 15 (24.2%) | 15 (24.2%) | 30 (24.2%) |
| Academic Level | | | |
| 3rd Year | 32 (51.6%) | 31 (50.0%) | 63 (50.8%) |
| 4th Year | 30 (48.4%) | 31 (50.0%) | 61 (49.2%) |
| Age Range | | | |
| 19-20 years | 14 (22.6%) | 15 (24.2%) | 29 (23.4%) |
| 21-22 years | 36 (58.1%) | 35 (56.5%) | 71 (57.3%) |
| 23-24 years | 12 (19.4%) | 12 (19.4%) | 24 (19.4%) |
| Experience with Adaptive Learning | | | |
| No experience | 52 (83.9%) | 54 (87.1%) | 106 (85.5%) |
| Minimal experience | 8 (12.9%) | 7 (11.3%) | 15 (12.1%) |
| Moderate experience | 2 (3.2%) | 1 (1.6%) | 3 (2.4%) |

*Source:* author's development

Descriptive statistics for pre-test scores showed similar baseline conditions between the two groups, with mean scores of 65.4 (SD = 8.6) for the experimental group and 64.8 (SD = 8.9) for the control group. However, significant differences were observed in the post-test results: the experimental group had a mean score of 87.2 (SD = 7.2), while the control group scored 72.6 (SD = 8.5), indicating greater improvement in the adaptive learning group. Pre-test score distributions were similar, with most students scoring in the 60-69 range (35.5% experimental; 38.7% control). Post-intervention, 80.6% of the experimental group scored 80 or higher, compared to 22.6% of the control group. The post-test range was narrower for the experimental group (30.0) than for the control group (38.0), indicating more homogeneous academic achievement after using adaptive learning. This descriptive analysis sets the stage for deeper inferential analysis of the effectiveness of AI-based adaptive learning versus traditional methods, as summarized in Table 4.

**Tabel 4**

Summary Statistics of Test Scores

| Statistics | Experimental Group (n=62) | | Control Group (n=62) | |
|---|---|---|---|---|
| | Pre-test | Post-test | Pre-test | Post-test |
| Mean | 65.4 | 87.2 | 64.8 | 72.6 |
| Standard Deviation | 8.6 | 7.2 | 8.9 | 8.5 |
| Minimum | 42.0 | 68.0 | 40.0 | 52.0 |
| Quartile 1 (Q1) | 58.5 | 82.0 | 57.5 | 66.0 |
| Median (Q2) | 66.0 | 88.5 | 65.0 | 73.0 |
| Quartile 3 (Q3) | 72.0 | 93.0 | 73.0 | 80.0 |
| Maximum | 85.0 | 98.0 | 82.0 | 90.0 |
| Range | 43.0 | 30.0 | 42.0 | 38.0 |
| Skewness | -0.24 | -0.68 | -0.31 | -0.22 |
| Kurtosis | 0.08 | 0.27 | 0.12 | -0.15 |
| Confidence Interval (95%) | 63.2 - 67.6 | 85.3 - 89.1 | 62.5 - 67.1 | 70.4 - 74.8 |

*Source:* author's development

***Comparison Between Groups (Adaptive Learning vs. Traditional Learning)***

The statistical analysis results indicate that adaptive learning significantly enhances student academic performance compared to traditional teaching methods. Table 1 compares pre-test and post-test scores between the experimental group (adaptive learning) and the control group (traditional methods).

Diving into the details in Table 5, the adaptive learning group saw an impressive 33.3% jump in their scores, climbing from an average of 65.4 to 87.2. On the other hand, sticking to traditional methods, the control group only managed a 12.0% increase, moving from 64.8 to 72.6. That is a striking 21.3% difference in improvement between the two groups. With a p-value < 0.01, it is clear that adaptive learning makes a significant difference in how well students grasp academic material.

**Table 5**

*Comparison of Pre-test and Post-test Scores*

| Group | Pre-test Score (Average) | Post-test Score (Average) | Increase (%) | p-value | Significance |
|---|---|---|---|---|---|
| Experimental (Adaptive Learning) | 65.4 | 87.2 | 33.3% | <0.01 | Significant |
| Control (Traditional Method) | 64.8 | 72.6 | 12.0% | <0.05 | Significant |
| Difference | 0.6 | 14.6 | 21.3% | <0.01 | Significant |

*Source:* author's development

Meanwhile, to test the significance of the differences between groups, an independent t-test was conducted, as shown in Table 6. The analysis showed no significant difference in the pre-test scores between the two groups ($p = 0.68$, $t = 0.42$), indicating that students had relatively the same initial level of understanding. However, after the intervention, there was a significant difference in the post-test scores ($p < 0.001$, $t = 4.86$) with a large effect size (Cohen's $d = 1.26$). In addition, the difference in gain scores ($p < 0.001$, $t = 5.32$, Cohen's $d = 1.37$) indicated that adaptive learning provided a much greater increase in understanding compared to traditional methods.

**Table 6**

*Results of Independent T-test*

| Parameter | t-value | Degrees of Freedom | p-value | Cohen's d (Effect Size) | Interpretation |
|---|---|---|---|---|---|
| Pre-test Score | 0.42 | 58 | 0.68 | 0.11 | No significant difference |
| Post-test Score | 4.86 | 58 | <0.001 | 1.26 | Significant difference with large effect |
| Gain Score | 5.32 | 58 | <0.001 | 1.37 | Significant difference with large effect |

*Source:* author's development

To dig deeper into what influences learning outcomes, we analyzed variance (ANOVA), factoring in additional elements like arithmetic and programming skills. As shown in Table 3, the results reveal that the learning method plays a significant role in academic performance ($F = 18.7$, $p < 0.001$), solidifying the idea that adaptive learning outshines traditional methods.

Interestingly, both arithmetic and programming skills also made a notable difference. Arithmetic skills had an F value of 4.8 ($p < 0.05$), while programming skills came in at $F = 5.8$ ($p < 0.01$). However, we found something intriguing when we looked at how these skills interacted with the learning method. The combination of the learning method and arithmetic skills didn't show a significant effect ($p = 0.09$), but the interaction between the learning method and programming skills did ($p < 0.05$). This indicates that programming skills are more crucial in making adaptive learning effective than arithmetic skills. For a detailed breakdown, check out Table 7.

**Table 7**

*ANOVA Results (Additional Factors)*

| Source of Variation | Sum of Squares | df | Mean Square | F-value | p-value | Significance |
|---|---|---|---|---|---|---|
| Learning Method | 1254.6 | 1 | 1254.6 | 18.7 | <0.001 | Significant |
| Arithmetic Ability | 645.3 | 2 | 322.65 | 4.8 | <0.05 | Significant |
| Programming Ability | 782.1 | 2 | 391.05 | 5.8 | <0.01 | Significant |
| Interaction (Method × Arithmetic) | 324.8 | 2 | 162.4 | 2.4 | 0.09 | Not significant |
| Interaction (Method × Programming) | 412.6 | 2 | 206.3 | 3.1 | <0.05 | Significant |
| Error | 3546.2 | 53 | 66.9 | - | - | - |
| Total | 6965.6 | 62 | - | - | - | - |

*Source:* author's development

Beyond looking at statistical significance, we also measured the practical impact of adaptive learning using Cohen's d. The findings, noted in Table 5, indicate adaptive learning has a substantial impact ($d > 0.8$) in all areas measured. This also includes large increases in academic achievement ($d = 1.26$), enhanced problem-solving ($d = 0.98$), and increased student engagement ($d = 1.14$). Given its overall effect size of $d = 1.13$, it is evident that adaptive learning profoundly and meaningfully impacts the improvement of student learning. For a more detailed analysis, a summary of the results is captured in Table 8, which details the adaptive learning training impact analysis.

**Table 8**

*Effect Size Analysis*

| Measurement | Cohen's d | Interpretation |
|---|---|---|
| Academic Improvement | 1.26 | Large effect (>0.8) |
| Problem-solving Skills | 0.98 | Large effect (>0.8) |
| Student Engagement | 1.14 | Large effect (>0.8) |
| Overall Effect | 1.13 | Large effect (>0.8) |

*Source:* author's development

The analysis of ANOVA and the calculation of the effect size indicate that adaptive learning facilitates better problem-solving skills, engagement levels, and academic performance. These results imply that, at least in electric engineering and automation, adaptive methodologies can be plausible alternatives to traditional pedagogical frameworks.

***Student Engagement and Feedback***

The survey data analysis demonstrated that there was a difference in student engagement in the context of both adaptive learning and traditional teaching methods. The adaptive learning group reported an engagement score of 4.2 on a 5.0 scale, while the control group scored only 3.4 ($p<0.01$). The striking inflexion occurred in the "interaction with the system/instructor" category, where the engagement effect size was 1.12. Also, the adaptive group performed better than the control group: 4.1 vs 3.2 ($p<0.001$). With a Cohen's d score of 1.04, the adaptive learning group's motivation was impacted compared to the control group.

**Table 9**

*Engagement and Motivation Survey Results*

| Indicators | Experimental Group (n=62) | Control Group (n=62) | Difference | p-value | Cohen's d |
|---|---|---|---|---|---|
| Engagement in Learning | | | | | |
| Activity in completing assignments | 4.3 | 3.6 | 0.7 | <0.01 | 0.91 |
| Consistency in completing materials | 4.2 | 3.5 | 0.7 | <0.01 | 0.88 |
| Interaction with the system/instructor | 4.1 | 3.2 | 0.9 | <0.001 | 1.12 |
| Level of attendance in learning | 4.5 | 4.2 | 0.3 | <0.05 | 0.45 |
| Average Engagement | 4.2 | 3.4 | 0.8 | <0.01 | 0.92 |
| Learning Motivation | | | | | |
| Enthusiasm for the material | 4.3 | 3.4 | 0.9 | <0.001 | 1.05 |
| Desire to learn additional material | 4.0 | 3.1 | 0.9 | <0.001 | 1.10 |
| Persistence in facing challenges | 4.1 | 3.3 | 0.8 | <0.01 | 0.94 |

| | | | | | |
|---|---|---|---|---|---|
| Initiative in learning | 3.9 | 3.0 | 0.9 | <0.001 | 1.08 |
| Average Motivation | 4.1 | 3.2 | 0.9 | <0.001 | 1.04 |
| Perception of Learning Effectiveness | | | | | |
| Understanding of concepts | 4.3 | 3.5 | 0.8 | <0.01 | 0.95 |
| Ability to apply practically | 4.2 | 3.4 | 0.8 | <0.01 | 0.97 |
| Achievement of learning targets | 4.3 | 3.6 | 0.7 | <0.01 | 0.85 |
| Quality of feedback received | 4.4 | 3.2 | 1.2 | <0.001 | 1.35 |
| Average Effectiveness | 4.3 | 3.4 | 0.9 | <0.01 | 1.03 |

*Source:* author's development

***Qualitative Feedback from Students & Instructors***

Students perceived an adaptive learning system to incorporate higher interactivity, flexibility, and responsiveness levels than traditional learning systems. Students valued receiving real-time feedback and support, allowing them to self-pace. This motivated and engaged electrical engineering and automation learners because the system adjusted to their skill levels. Students were also more motivated and engaged in other subjects because the difficulty level was adjusted to suit their skill level. On the other hand, adapting to the system was highlighted as a challenge alongside dependable internet access.

From an instructor's perspective, adaptive learning altered the students' patterns of interaction significantly. Students in the experimental group became more active in the class, participating more, asking questions and demonstrating an understanding of the technical concepts. Instructors valued the analytics that came with the class and how detailed the summary analyses were about evaluating student progress. Untrained instructors unfamiliar with using the system also had challenges, as students who learned under traditional methods required more time to adapt to the new system.

The feedback provided by students and instructors was analyzed using word clouds to pinpoint the most commonly used terms highlighted visually throughout the entire feedback system. Student responses showcased dominant words such as "interactive," "flexible," 'motivation," "real-time feedback," and "personalized", which suggest that adaptive learning is considered a more effective and fluid approach to pedagogy. Meanwhile, instructors focused on "high engagement," "quick response," "more accurate evaluation," and "changing interaction patterns," which illustrate the system's advantages in teaching and academic evaluation. These findings reinforce the conclusion that adaptive learning not only enhances the student learning experience but also positively impacts teaching methods and evaluation processes for instructors.

**Figure 1**

*Word Cloud Analysis*


*Source:* author's development

The results indicated that adaptive learning significantly enhanced students' academic performance, problem-solving skills, and engagement compared to traditional methods. The experimental group saw an average post-test score increase of 33.3%, compared to the control group's 12.0% ($p < 0.001$, Cohen's $d = 1.26$). Active participation was higher in the adaptive learning group (84.7%) versus traditional methods (62.3%), with key engagement factors being material personalization (87.1%), real-time feedback (82.3%), and flexible learning pace (78.5%). However, challenges included a steep initial adaptation curve (35.5% of students faced difficulties) and technical issues like limited internet infrastructure. Instructors also reported longer content development times (averaging 3.2 times longer) and the need for additional technical training. Notably, visual and kinesthetic learners benefited more than auditory learners, and improvements in self-directed learning persisted even after the study, highlighting a positive long-term impact on study habits.

## Discussion

The results of this study affirm that adaptive learning significantly enhances academic performance, problem-solving skills, and student engagement compared to traditional teaching methods. The higher post-test scores observed in the experimental group (33.3% vs 12.0%, $p < 0.001$, Cohen's $d = 1.26$) indicate that AI-based learning systems are capable of adjusting difficulty levels and providing real-time feedback, enabling students to comprehend the material more effectively (El-Sabagh, 2021). Moreover, the significant enhancement in problem-solving abilities observed in the adaptive group (28.5% compared to 14.2%) indicates that tailored learning approaches and self-regulated learning positively influence the analytical skills of engineering students. In terms of engagement, students utilizing adaptive learning methods exhibited a higher level of active participation (84.7%) than their counterparts in traditional educational settings (62.3%). Their primary sources of motivation included personalized content (87.1%), immediate feedback (82.3%), and the ability to learn at their own pace (78.5%). Nonetheless, this research also highlights the challenges associated with adaptive learning, such as a steep initial adjustment period, with 35.5% of students facing difficulties during the first two weeks, as well as constraints related to technological infrastructure that can hinder the learning experience (Lim et al., 2020). Consequently, these results reinforce constructivist and self-regulated learning theories within engineering education and offer valuable insights into optimizing adaptive learning to improve the effectiveness of technology-enhanced curricula.

Adaptive learning technologies and online environments have demonstrated promising potential in enhancing student engagement and learning outcomes in higher education. Studies indicate that web-based platforms and adaptive systems based on learning styles foster higher engagement than conventional methods (Chen et al., 2010; El-Sabagh, 2021). Personalized learning paths created using adaptive algorithms are strongly associated with improvements in student retention, motivation, and academic achievement (Peng et al., 2019). Furthermore, interest-based personalization has improved problem-solving efficiency, particularly for students who struggle with traditional approaches (Walkington, 2013). However, challenges remain in measuring engagement meaningfully in online environments and in addressing disparities in participation caused by inequitable digital access (Henrie et al., 2015; Paulsen & McCormick, 2020).

These findings deepen the theoretical framework within engineering education by reinforcing the effectiveness of adaptive learning in promoting student-centred outcomes and essential 21st-century skills. Prior research has validated the role of AI-driven adaptive learning in enabling the customization of instructional content to meet diverse learner profiles, thereby improving participation and outcomes (Puspitarini & Hanif, 2019; Ogunbiyi et al., 2021). Adaptive learning also supports greater autonomy by empowering students to manage their own learning pathways. Nonetheless, various studies reveal that its impact on engagement can be conditional and largely influenced by instructional design quality and educator readiness to implement adaptive methods effectively. Moreover, the lack of infrastructure, digital fluency, and consistent internet access continues to pose barriers in some educational contexts.

Despite these challenges, adaptive learning remains a promising approach in engineering education, particularly in fields like electrical and automation engineering. Its ability to personalize learning sequences and provide feedback aligned with students' real-time understanding makes it highly suitable for supporting skills development aligned with the demands of Industry 4.0 and 5.0. Students trained with adaptive learning systems often demonstrate higher motivation and deeper engagement, which helps overcome the rigidities of traditional instruction (Masdoki et al., 2021; Hsu & Lin, 2020). Therefore, it is recommended that universities and technical institutions explore the integration of adaptive learning with blended formats that combine AI-supported systems with physical labs and project-based activities relevant to real-world applications.

However, successful implementation depends not only on technology but also on institutional preparedness and instructor training. Adaptive content development requires significantly more time and effort compared to conventional approaches (Ifenthaler, 2012), highlighting the importance of supporting educators in adopting these methods. Furthermore, ensuring equitable access to Internet infrastructure is critical for inclusive and effective adaptive learning environments. Coordinated efforts from all academic stakeholders are necessary to create responsive curricula that anticipate both student needs and evolving industry demands, ultimately promoting adaptability and resilience in engineering education.

## Conclusions

The development of adaptive technologies has dramatically enhanced education, particularly in engineering, by improving achievement, problem-solving abilities, and engagement through personalized learning, real-time feedback, and content-specific self-paced learning. Compared to the control, the experimental group's post-test score improvement was 33.3% versus 12.0% in the control group, with strong statistical significance ($p < 0.001$). Moreover, students using the adaptive learning system demonstrated greater participation (84.7% vs. 62.3%), partly attributable to the autonomy they experienced within the system, the adaptive nature of the learning materials, and immediate feedback.

### *Suggestions for future research*

These results emphasize the need for adopting new approaches in engineering education. Academic institutions must start utilizing adaptive learning technologies through AI-driven platforms, blended teaching models, or integrating more interactive, data-driven teaching aids into curricula. There is a need for education policymakers at the tertiary level to focus on improving the digital infrastructure of the institution and the availability of training for instructors for effective use of adaptive learning technologies to enhance broader implementation. Further research should focus on the long-term impacts of adaptive learning on industry preparedness, diverse learning styles, and strategies for optimal content creation to apply technology in learning engineering education.


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