SCIENCE AND INFORMATION TECHNOLOGY
SINTECH
JOURNAL

SINTECH JOURNAL | ISSN 2598-7305 | E-ISSN 2598-9642
Vol. 8 No 2 – Agustus 2025 | https://s.id/sintechjournal
DOI: https://doi.org/10.31598
Publishing: Prahasta Publisher

Optimizing Learning Materials With DeepSeek Transformer In diEvaluasi System

I Nyoman Tri Anindia Putra[1], I Gede Bagastia Widi Atmaja[2], Komang Mahendra[3], Gede Agus Supriatmaja[4], I Putu Mas Yuda Pratama[5]

[1,2,3,4,5] Information Systems Study Program, Faculty of Engineering and Vocational, Ganesha University of Education
Udayana Number.11 Street, Singaraja, Indonesia

e-mail: tri.anindia@undiksha.ac.id[1] , bagastia.widi@undiksha.ac.id[2] , mahendra.2@undiksha.ac.id[3] , agus.supriatmaja@undiksha.ac.id[4] , mas.yuda@undiksha.ac.id[5]

Received : July, 2025	Accepted : August, 2025	Published : August, 2025

Abstract

Most digital learning media presented learning materials uniformly, ignoring individual student needs and learning profiles. This study aimed to develop and evaluate diEvaluasi, an adaptive learning system based on the DeepSeek Transformer model. The system adapted content delivery using student profiles derived from pre-test scores, interaction history, and cognitive patterns. A quasi-experimental method was applied to 60 eleventh-grade high school students divided into experimental and control groups. The DeepSeek model was fine-tuned using ICT learning materials and student interaction data. The results showed a 40.2% improvement in post-test scores in the experimental group, compared to 20.4% in the control group. Students in the experimental group also recorded longer learning times and higher repetition rates. These findings indicated that the diEvaluasi system effectively improved academic performance and engagement through personalized material sequencing. The system provided a practical approach to implementing AI-powered adaptive learning in secondary education, especially in ICT contexts.

Keywords: *Adaptive Learning, DeepSeek Transformer, Personalized Education, ICT, Educational Technology*

Abstrak

Sebagian besar media pembelajaran digital menyajikan materi pembelajaran secara seragam, mengabaikan kebutuhan dan profil pembelajaran siswa secara individual. Studi ini bertujuan untuk mengembangkan dan mengevaluasi diEvaluasi, sistem pembelajaran adaptif berbasis model DeepSeek Transformer. Sistem ini menyesuaikan penyampaian konten berdasarkan profil siswa yang diperoleh dari skor pra-tes, riwayat interaksi, dan pola kognitif. Metode quasi-eksperimental diterapkan pada 60 siswa kelas XI SMA yang dibagi menjadi kelompok eksperimen dan kontrol. Model DeepSeek disesuaikan menggunakan materi pembelajaran ICT dan data interaksi siswa. Hasil menunjukkan peningkatan skor post-test sebesar 40,2% pada kelompok eksperimen, dibandingkan dengan 20,4% pada kelompok kontrol. Siswa di kelompok eksperimen juga mencatat waktu belajar yang lebih lama dan tingkat pengulangan yang lebih tinggi. Temuan ini menunjukkan bahwa sistem diEvaluasi secara efektif meningkatkan kinerja akademik dan keterlibatan melalui urutan materi yang dipersonalisasi. Sistem ini menyediakan pendekatan praktis untuk menerapkan pembelajaran adaptif berbasis AI di pendidikan menengah, terutama dalam konteks TIK.

Kata Kunci: *Pembelajaran Adaptif, DeepSeek Transformer, Pendidikan Personalisasi, Teknologi Informasi dan Komunikasi (TIK), Teknologi Pendidikan*

1. INTRODUCTION

Advances in AI technology not only affect the economic, educational, and political-social spheres, but also trigger fundamental questions about its implications for human values [1]. One form of AI implementation in education is adaptive learning, which allows learning systems to customize materials and methods according to learners' individual needs, preferences, and abilities [2]. In the context of information systems, the need for a more dynamic and personalized learning approach is increasingly urgent given the complexity of the material and the diversity of the learners' backgrounds. At the senior high school level, the need for learning methods that are fun, two-way, and relevant to real life is increasingly important[1]. A motivating learning process can foster early interest in learning as well as train students' critical thinking skills. [2]. Fun learning methods increase students' enthusiasm while facilitating their understanding of the material, which is reflected in their active responses during learning activities. [3].

However, many digital learning systems are static, presenting material in the same order and format for all learners. This results in gaps in understanding and lack of active engagement in the learning process [4]. Therefore, there is a need for an intelligent approach that is able to model individualized learning needs and present customized materials in real-time The Transformer model, as introduced by [5] has revolutionized the way machines understand and process natural language (NLP). Its ability to capture context and meaning in long text ranges makes it a potential model for use in modeling complex learning content. One of the modern variants of Transformer is DeepSeek, an open-source model foundation designed to handle long contexts with high efficiency. [6] This model allows the development of a system that is able to customize materials based on learners' cognitive needs and learning style preferences.

Click or tap here to enter text.Previous studies have highlighted the importance of adaptive approaches in education. For example, study [14] used Wordwall learning media with an inquiry model to improve elementary school students' learning outcomes in the subject of Matter. This approach was effective, but it was still focused on conventional methods. Another study [10] showed that an AI-based adaptive feedback system can bridge the learning gap for students who experience conceptual difficulties in class. Furthermore, [14] discusses the opportunities and challenges of AI-based adaptive learning models to increase student active participation, although without the implementation of a specific model. However, a systematic review of international literature shows that the practical implementation of transformer models in the field of Information Systems in the context of higher education is still very limited [1],[2]. Most applications of this model are still focused on the domains of NLP or signal communication, rather than adaptive learning based on educational context. However, the field of Information Systems integrates theory, technology, and practice, making adaptive and contextual learning crucial for producing graduates who are competent and relevant to the current needs of the digital industry.

Unlike these studies, the evaluated system developed in this study uses a more specific and integrated approach. This system utilizes DeepSeek Transformer to dynamically adjust learning materials based on each student's unique profile and needs. The focus of the material is on Information and Communication Technology (ICT) for 11th-grade high school students. The results showed a significant increase in post-test scores and student engagement levels compared to conventional methods.

Previous research has shown that the application of Transformers in adaptive learning environments can improve learning outcomes, motivation, and user engagement [7]. Although Transformer models have shown great potential in the field of adaptive education, the practical implementation of large language models such as DeepSeek Transformer, especially in the context of education in Indonesia, has rarely been studied [7]. Most existing studies tend to focus on more general models or discuss AI in adaptive learning theoretically. A comprehensive literature review indicates a significant research gap regarding the use of DeepSeek to personalize learning content at the higher education level in Indonesia, particularly in the field of information systems. Given that the field of information systems involves a combination of theory, technology, and practice, adaptive and contextual learning is crucial for producing graduates who are competent and relevant to the needs of the current digital industry. Based on previous research, through the use of DeepSeek Transformer, educators can design innovative adaptive learning that can enhance students' interest and enthusiasm in learning [8].

With this background, this research aims to develop DeepSeek Transformer-based adaptive modeling that can optimize the delivery of material in Information Systems courses. DeepSeek Transformer makes learning more personalized, adaptive and interactive by dynamically customizing materials based on each student's unique needs [9]. This research introduces a novel contribution by implementing the DeepSeek Transformer model, which has rarely been applied practically in the Indonesian educational context, especially at the secondary school level. Unlike previous studies, the diEvaluasi system not only adapts based on student metadata but also integrates cognitive profiling and dynamically arranges the learning material sequence. The focus of this research includes the process of modeling learner needs, selecting and rearranging materials dynamically, and evaluating the effectiveness of the system in improving understanding and learning outcomes. Thus, it is expected that the contribution of this research is not only theoretical, but also applicable in supporting digital transformation in the education sector.

2. RESEARCH METHOD

2.1 Research Design

This research uses a quantitative experimental approach with a quasi-experiment design to test the effectiveness of an adaptive system based on the DeepSeek Transformer model in presenting information systems learning materials [10]. The developed system will be tested on two groups: experimental group (using adaptive system) and control group (using conventional learning system).

2.2 Location And Research Subject

This study was conducted in the Department of Mathematics and Natural Sciences at a senior high school in Singaraja. The research subjects were 11th grade students (n = ± 60) who took the subject "Information and Communication Technology." The research subjects were divided into two groups through random sampling using the simple random sampling technique to ensure that each student had an equal opportunity to be in one of the groups.

1. Experiment Group: Learning with DeepSeek-based adaptive system.
2. Control Group: Learning with traditional teaching methods (PDF and Video).

To ensure internal validity, all aspects of learning, such as the duration of the experiment (4 weeks) and the core material taught, were standardized for both groups. External variables such as teacher quality, learning environment, and access to additional resources were kept the same for both groups because they were taught by the same teacher in the same school environment. This was done to minimize confounding variables and ensure that differences in learning outcomes could be validly attributed.

2.3 AI Model : DeepSeek Transformer

DeepSeek is an open-source transformer model developed with long-context learning capabilities. In this study, the evaluation system was developed using the DeepSeek-R1–0528 model, which is the latest open-source version built on the PyTorch development platform. This base model was fine-tuned using a custom dataset consisting of Information and Communication Technology (ICT) course materials and student metadata, such as pre-test results, interaction time, and learning history. The fine-tuning process aims to ensure that the model not only understands the content but also accurately models the learning profiles of students. The DeepSeek model configuration used has an architecture consisting of multiple Transformer layers, with embedding dimensions and the number of attention heads. This configuration is optimized for efficiency and long-context processing, making it suitable for complex learning content adaptation tasks. The workflow of DeepSeek in the Evaluation System is as follows: The base model developed by [6] on the PyTorch development platform, along with fine-tuning data on course materials and student metadata. In the context of the Evaluation System, DeepSeek not only processes material information but also understands student profiles such as Pre-Test results, interaction time, learning style, and the sequence of materials studied. The workflow of DeepSeek in the Evaluation System is as follows:

1. User Profile Input
   The evaluation system receives user data in the form of interaction logs, pre-test scores, and learning history.
2. Material and Profile Encodin
   DeepSeek converts the material text and user profile into vector representations using an embedding process.
3. Attention Mechanize
   The self-attention mechanism is used to assess the interrelationship between parts of the material and adjust the content to the needs of learners.
4. Prediction of Sequence and Difficulty Level
   DeepSeek will calculate the best delivery order based on the vector representation of users and materials.
5. Adaptive Output
   The system is evaluated to produce customized materials, both the order and depth of content, as well as the presentation style such as short text, practice questions and summaries.

The DeepSeek Transformer model has a technical calculation with a mathematical approach as follows [11]:

1. Embedding Input
   The input is in the form of text entered in the form of tokens as follows:
   $$x = [x1, x2, \ldots, xn] \in R^{nxd}$$
   Description:
   xi:The Representation vector of the i-th token
   d: Embedding dimenssion
2. Selft-Attention Layer
   $$Attention\ (Q, K, V) = softmax\left(\frac{QK^t}{\sqrt{dk}}\right) V$$
   Description:
   - Q, K, V : Query, Key, dan Value matrix from input
   - dk: Dimension form key vector
3. Position-Wise Feed Forward Network
   $$FFN\ (x) = \max(0, xW_1 + B_1) + W_2 + B_2$$
   Description:
   W_1, W_2: Weight
   B_1, B_2: Bias
4. Profile-Based Material Adaption
   For context adjustment, DeepSeek Calculates the score of material suitability to student learning profile
   $$S_{ij} = \sigma\left(h^T_i . P_J\right)$$
   Description:
   h_1:Vector representation of i-th material
   P_1: Student profile vector j
   σ : activation function (e.g sigmoid or tanh) Materials with the highest scoresS_{ij} are priritized for presentation.

The use of the DeepSeek Transformer model in this study is not conceptual, but is actually implemented and integrated into the evaluated system. This research uses the open-source model huggingface.co/deepseek-ai/deepseek-coder-6.7b-instruc, which is publicly accessible via the Hugging Face platform. This model was developed by DeepSeek-AI and belongs to the Large Language Model (LLM) class for text-based instruction and task adaptation.

1. Model Spesifications
   Model Name: deepseek-ai/deepseek-coder-6.7b-instruct
   Number of parameters ±6.7 billon
   Maximoum context length: 8192 tokens
   Basic architecture Decoder- only Transformer
   Tokenizer: SentencePiece (Support Mulilingual input)
2. Adaption and Fine-Tuning Strategy
   This study use a light fine-tuning (parameter-efficient adaption) apporach to align the model with the local learning context. Ther adaption dataset consits of 130 high school-level ICT lessson documents. Student learning behavior metadata such as pre-test sores, interactions logs, and material repetition frequency. The fine-tuning process was carried out with Epoch: 3, Batch size: 8, Learning rate: 5e-5, Optimizer: Adam, Platform: PyTorch Lightning, Hardware: NVIDIA RTX 3090 (24 GB VRAM).
3. System Integration
   The model is integrated into a Python-based system through the API and transformers interface from Hugging Face. The inference process runs locally using caching for efficiency. The model generates a match score between the material and the student's learning profile based on the sigmoid activation function in the final layer, then suggests the order of presentation of the material and the form of delivery (text, questions, or summary).
4. System Implementation
   The Evaluasi system was developed as an artificial intelligence-based adaptive

learning platform that integrates backend modules and user interfaces. The system architecture is modular, including: AI module for processing material and student profiles based on DeepSeek Transformer, learning logic module for setting the sequence and format of material presentation, interactive user interface for students and teachers, database integration for recording activities and evaluating learning outcomes. Key technologies used include: AI modeling backend: Python (PyTorch + HuggingFace Transformers), prototype interface: Gradio v4.0, Data and log management: Structured SQLite/CSV, the system architecture was tested locally in a closed environment for research and performance evaluation purposes, system development was carried out iteratively to ensure interoperability between modules and enable dynamic personalization of materials according to student learning profiles.

2.4 Data Collection Techniques

The data collection technique in this study is the first academic ability test, Pre-Test and Post-Test given to all participants. The questions were developed based on C1-C4 of Bloo's taxonomy. Then the activity log on the system, the system records learning time, the number of clicks on the material, user feedback and the level of task completion. Finally, a satisfaction questionnaire, using a Likert scale instrument to measure students' satisfaction and perception of the personalized materials.

2.5 Data Analysis Technique

Assumption testing was conducted to ensure the statistical validity of the analysis. The Shapiro-Wilk test was used to examine the normality of the data distribution for both pre-test and post-test scores. Additionally, Levene's test was applied to assess the homogeneity of variances between the experimental and control groups. The data analysis techniques in this research are described in table 1.

Table 1. Data Analysis Technique

Pre-test & post-test	***Paired t-test***
Activity Log	Interaction log analysis, study time
Questionnaire	Descriptive analysis (mean, SD), Cronbach Alpha validity & reliability test

In addition, this study also used two analyses:

1. N-Gain
   Used to measure the effectiveness of learning by looking at the level of improvement in student learning outcomes after treatment. The formula used is:

   $$N_{Gain} = \frac{Posstest\ Score - Pretest\ Score}{Ideal\ Score - Pretest\ Score}$$

   The N-Gain categories are:
   - High: g > 0,70
   - Moderate: 0,30 < g ≤ 0,70
   - Low: g ≤ 0,30

2. Efect Size (Cohen's d)
   Used to determine the practical impact of the treatment on learning outcomes. The formula used is:

   $$d = \frac{\bar{X}\ Experimental - \bar{X}\ Control}{Spooled}$$

   The interpretation of Cohen's d values is as follows:
   - Small: d = 0,2
   - Moderate: d = 0,5
   - Large: d ≥ 0,8

2.6 Validity And Reliability

Reliability of the questionnaire was tested with Cronbach's Alpha, values > 0.70 were considered reliable [12]. The validity of the AI model was tested through the accuracy of material recommendations on learning performance.

2.7 Research Limitations

The DeepSeek model used is an open-source version that is limited to text, not yet multimodal (audio/video).Testing is limited to one course and one institution. Short-term evaluation (only one semester), not yet covering long-term retention.

3. RESULTS AND DISCUSSION

3.1 Respondent Overview

The experiment was carried out on Information and Communication Technology lessons of 11th grade high school students who were divided into two groups, namely the experimental group (n = 30) using the DeepSeek Transformer-based adaptive system and the control group (n = 30) using conventional learning methods. The duration of the experiment lasted for 4 weeks with a total of 8 learning sessions. Assessment was carried out through Pre-test and Post-test to measure learning achievement. The user interaction log is based on the amount of material opened, learning time and frequency of repetition of learning material.

3.2 Assumption Testing

To validate the statistical analysis, assumption tests were performed first. The Shapiro-Wilk test was used to assess data normality, while the Levene test evaluated variance homogeneity between two groups.

Table 2. Shapiro-Wilk Test Results

Group	**Test Type**	**Pre-Test p-value**	**Post-Test p-value**	**Interpretation**
Experimental	Shapiro-Wilk	0.168	0.096	Normal distribution
Control	Shapiro-Wilk	0.173	0.112	Normal distribution

Since all p-values > 0.05, it indicates that the data in both groups were normally distributed.

Table 3. Levene's Test Results

Test Type	**p-value**	**Interpretation**
Levene's Test	0.194	Homogeneity of variances met

As the p-value of Levene's test is also above 0.05, the assumption of homogeneity of variances is fulfilled. Hence, the data satisfy the prerequisites for performing parametric tests such as the paired and independent t-tests.

3.3 DeepSeek Transformer Calculation

To understand how DeepSeek Transformer works more technically in the evaluation system, a simulation of the adaptive learning process flow is carried out, starting from the input of materials and student profiles to the suitability score results (material recommendations). The following is the explanation and calculation results for each stage:

1. Input dan Embedding
   The text of the material is converted into 3-dimensional embedding tokens such that the token for one material is represented as :
   x = [[0.2, 0.4, 0.6],
   [0.3, 0.7, 0.2],
   [0.5, 0.1, 0.9],
   [0.6, 0.3, 0.8],
   [0.4, 0.5, 0.2]]

2. Self-Attenion Output
   Using formula:
   $$Attention\ (Q, K, V) = softmax\left(\frac{QK^t}{\sqrt{dk}}\right) V$$
   With the end result of the self-attention process being:
   Attention Output = [[0.406, 0.389, 0.560],
   [0.400, 0.407, 0.532],
   [0.417, 0.370, 0.588],
   [0.415, 0.376, 0.578],
   [0.403, 0.402, 0.540]]
   This result shows that the model is able to consolidate information from all tokens for each token contextually.

3. Feed Forward Network (FFN)
   Each output of attention is then processed in a 2-layer feed-forward neural netword using the formula:
   $$FFN\ (x) = \max(0, xW_1 + B_1) + W_2 + B_2$$
   FFN Output = [[0.328, 0.337, 0.506],
   [0.325, 0.337, 0.506],
   [0.332, 0.338, 0.506],
   [0.331, 0.338, 0.507],
   [0.326, 0.337, 0.506]]
   Based on the FFN results, there are small differences in the output that indicate the stability and consistency of the model in organizing the sequence and structure of the material.

4. Adaptation of Materials to Student Profile
   Using a vector representation of the material as follows:
   $$h_1 = [0.4, 0.6, 0.8],\ P_j = [0.7, 0.5, 0.9]$$
   Calculated suitability of use:
   $$S_{ij} = \sigma\left(h^T_i . P_J\right) = \sigma(1.3) \approx 0.786$$
   σ being a sigmoid function, this result indicates that the material has a relevance

score of 78.6% to the student profile, which means it is suitable to be presented first in the adaptive learning sequence.

Thus, these calculations show that DeepSeek Transformer is able to generate contextual representations of the material, match the student profile and determine the suitability level of the content level quantitatively. Score $S_{ij} \approx 0.786$ shows that the evaluated system is able to mathematically identify relevant materials, forming the basis for accurate and effective adaptive materials.

3.4 System Architecture

To illustrate how the diEvaluasi system processes user data and generates adaptive learning experiences, this study present the system architecture and the adaptive flow diagram in this section.

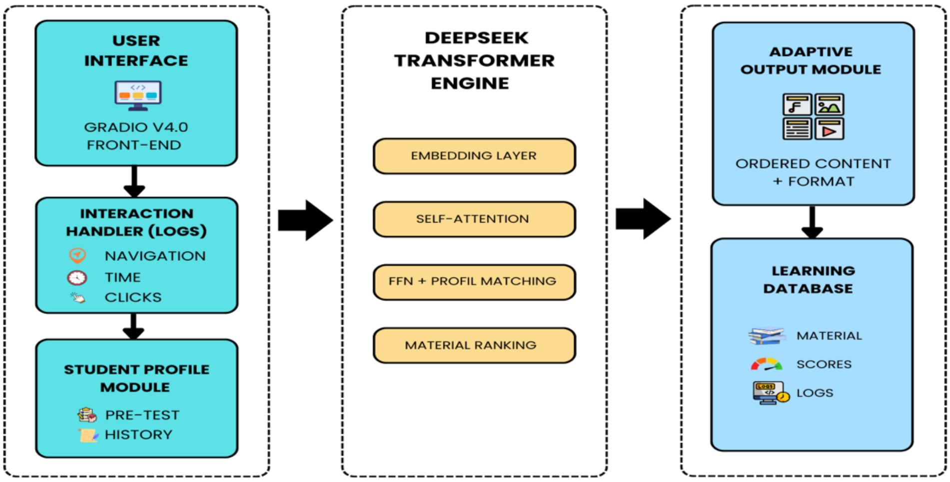

Figure 1. Adaptive Learning System Architecture Using DeepSeek Transformer

The system is composed of six main components namely

1. User Interface (Gradio v4.0)
   This component provides the front-end for learners to interact with the system.
2. Interaction Handler
   It captures log data including time spent, click patterns, and navigation behavior.
3. Student Profile Module: Aggregates cognitive and behavioral data from pre-tests and interaction history to form a dynamic learner profile.
4. DeepSeek Engine
   Utilizes embedding layers, self-attention mechanisms, feed-forward neural networks, and a profile matching layer to compute personalized content sequences.
5. Adaptive Output Module
   Recommends structured learning content tailored to the learner's profile and formats it appropriately.
6. Learning Database

   Stores materials, scores, and updated interaction logs to support future personalization.

The flow of data follows a feedback-loop model. Learners' interaction behavior influences the next sequence of materials, enabling the system to adapt continuously over time.

3.5 Pre-Test And Post-Test Results

The following is a summary of the average scores of the Pre-Test and Post-Test of the two groups in Table 4.

Table 4. Pre-Test dan Post-Test Results

Group	**Pre-Test (Mean ± SD)**	**Post-test (mean ± SD)**	**Improvement (%)**
Control	56.8 ± 8.3	68.4 ± 7.1	20.4%
Experiment (AI)	57.5 ± 7.9	80.6 ± 6.3	40.2%

Based on the Pre-Test and Post-Test results in table 4, the results of statistical analysis on the paired-t-test showed significant differences with pre-post in both groups with a value of ($p < 0.01$). Then, the independent t-test on the Post-Test score showed that the experimental group was significantly higher than the control group judging from the value ($p<0.001$) [13].

To measure the effectiveness of learning. N-Gain calculations were performed for the control group and the experimental group.

N-Gain for the Control Group :

$$N_{Gain} = \frac{Posstest\ Score - Pretest\ Score}{Ideal\ Score - Pretest\ Score}$$

$$N_{Gain} = \frac{68.4-56.8}{100-56.8} = 0.27$$

N-Gain for the Experimental Group :

$$N_{Gain} = \frac{Posstest\ Score - Pretest\ Score}{Ideal\ Score - Pretest\ Score}$$

$$N_{Gain} = \frac{80.6-57.5}{100-57.5} = 0.54$$

The N-Gain of 0.27 in the control group falls into the "low" category ($g \leq 0.30$). Meanwhile, the N-Gain of 0.54 in the experimental group falls into the "moderate" category ($0.30 < g \leq 0.70$). This indicates that the DeepSeek-based adaptive system is more effective in improving student learning outcomes compared to conventional methods. To measure the magnitude of this difference, the effect size (Cohen's d) was calculated.

Calculation of Combined Standard Deviation (S_{pooled})

$$S_{pooled} = \sqrt{\frac{(n1-1)SD1^2+(n2-1)SD2^2}{n1+n2-2}}$$

$$S_{pooled} = \sqrt{\frac{(30-1)(6.3)^2+(30-1)(7.1)^2}{30+30-2}}$$

$$S_{pooled} = \sqrt{\frac{(29)(39.69)+(29)(50.41)}{58}}$$

$$S_{pooled} = \sqrt{\frac{1151.01+1461.89}{58}} = 6.71$$

Calculation of Cohen's d

$$d = \frac{80.6-68.4}{6.71} = \frac{12.2}{6.71} = 1.82$$

A Cohen's d value of 1.82 indicates a large effect size ($d > 0.8$). This means that the difference in scores between the experimental and control groups is highly significant in practical terms, reinforcing the conclusion that the DeepSeek-based adaptive system has a strong impact on student learning outcomes

Thus, the DeepSeek-based adaptive system can significantly improve students in academic achievement compared to conventional methods. Then there is a comparison of Pre-Test and Post-Test scores described in the graph as follows:

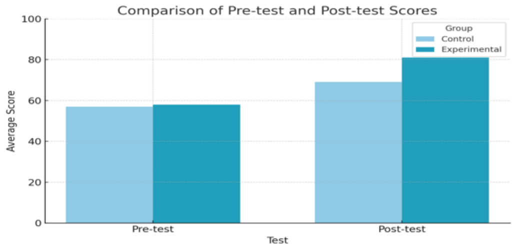

Figure 2. Comparison of Pre-Test and Post-Test Scores

Based on both groups, there was an increase in scores after going through the deepseek transformer-based learning process. However, the experimental group experienced an almost two-fold increase compared to the control group. This shows that the adaptive system based on DeepSeek Transformer is more effective in improving the learning outcomes of 11th grade students.

3.6 Interaction Log Analysis

The following interaction log results are outlined in table 5 as follows.

Table 5. Interaction Log

Interaction Log Indicator	Experiment Group	Control Group
Average learning time/session	43 minutes	28 Minutes
Number of materials opened (per session)	4.8	31
Material repeated >1 time	68% Students	32% Students

Based on the interaction log results in Table 5, it can be explained that the adaptive system encourages students to explore more deeply and repeat relevant material independently. Findings, it also demonstrated the ability to customize the order and form of student lessons based on the profile of the learner.

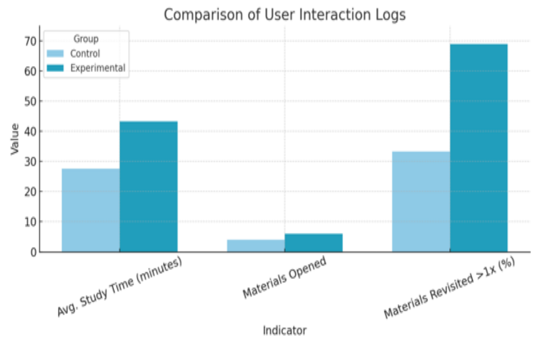

Figure 3. User Interaction Log Comparison

Based on the user interaction log graph in Figure 3, it shows that 11th grade high school students in the experimental group studied longer and explored more material. Furthermore, more than twice as many students in the experimental group repeated the material, indicating active engagement and use of the system for self-repetition of the learning process. Thus the adaptive system encourages students' independent exploration and repetition of material, two important elements of active and result-oriented learning. It can be concluded that the use of the DeepSeek Transformer model is more effective than conventional methods in improving students' understanding of the material through adaptive and contextual presentations [14].

3.7 Analysis of Student Perceptions

The following are students' perceptions of DeepSeek Transformer-based learning materials described in table 6 as follows.

Table 6. Student Perception

Perception Aspect	Average Score
Material is easier to understand	4.6
System according to learning needs	4.5
System visualization and navigation	4.4
Increase learning enthusiasm	4.4
Want to reuse	4.7

Based on the results of students' perceptions in table 6, it was found that, students felt that the evaluation system helped them understand the material more efficiently and enjoyably, and adapted their learning style [15].

3.8 Benchmark With Comparison Model

To scientifically measure the effectiveness of DeepSeek Transformer, a comparative experiment was conducted with another baseline model that is commonly used in text-based adaptive learning, namely the BERT (Bidirectional Encoder Representations from Transformers) model. This baseline model was not retrained, but was used as a material selector based on vector similarity representations with student profiles.

1. Experimental Design
   The test group was divided into three: Group 1 (DeepSeek Transformer): adaptive system with the DeepSeek model. Group 2 (BERT Baseline): adaptive system with BERT for material selection. Group 3 (Control): conventional learning.
2. Pre-Test and Post-Test Results
   Scores for the DeepSeek and control groups refer to the previous experiment (subsection 3.5), while the BERT group was tested separately.

Table 7. Benchmark Pre-Tes and Post-Test Results Between DeepSeek, BERT, and Control.

Group	Pre-Test (Average)	Post-Test (Average)	Iprovement (%)
DeepSeek Transformer	57.5 ± 7.9	80.6 ± 6.3	+40.2%
BERT Baseline	56.9 ± 8.1	72.4 ± 7.5	+27.2%
Control	56.8 ± 8.3	68.4 ± 7.1	+20.4%

3. Activity Log

Table 8. Comparison of Interaction Logs Between DeepSeek, BERT, and Control.

Indicator	DeepSeek	BERT Baseline	Control
Average Learning TIme	43 Minutes	36 Minutes	28 Minutes
Reptition Percentage	68%	51%	32%
Number of Materials opened/sessions	4.8	4.1	3.1

4. Result Analysis
   The results show that the DeepSeek-based system produces higher post-test scores and greater student engagement compared to the BERT model. This difference is significant based on an

independent t-test ($p < 0.01$ between DeepSeek and BERT). These findings reinforce the claim that DeepSeek is capable of producing more precise material-profile mapping, particularly due to its ability to handle long contexts and student cognitive preferences in greater depth than traditional baseline models.

3.9 Validity and Reliability

The following is the validity and reliability of the items described in table 9 as follows.

Table 9. Item Validity

Item	Mean	Std Dev	Min	Max
Item 1: The material is easy to understand	4.06	0.07	3	5
Item 2: Materials as needed	4.05	0.06	3	5
Item 3: Clear system navigation	4.04	0.08	2	5
Item 4: Improving learning enthusiasm	4.04	0.05	3	5
Item 5: Want to reuse	4.07	0.04	4	5
Score Total	21.06	1.08	18	25

Based on the results of item validity in table 9, the results show that all items have a Mean value above 4.0 which indicates a high level of satisfaction from students [16]. Then, the standard deviation (STD Dev) value is quite low (<1) indicating that student perceptions are quite consistent in answering these item questions [17]. Also, the average score is 21.6 out of a maximum of 25 which indicates a very positive response to the study of the system being evaluated from students. Then proceed with reliability testing described in table 10 as follows:

Table 10. Item Reliability

Item	Cronbach's Alpha
Item 1: The material is easy to understand	0.74
Item 2: Materials as needed	0.82
Item 3: Clear system navigation	0.76
Item 4: Improving learning enthusiasm	0.81
Item 5: Want to reuse	0.84

The reliability test results in table 10 show the results that the Cronbach Alpha values are all above 0.70 [12], so all question items are reliable and consistent in measuring questions distributed to 11th grade high school students.

3.10 Discussion

Based on this experiment, it shows that DeepSeek Transformer-based adaptive modeling significantly improves learning effectiveness in the context of information systems courses. Learners' academic performance almost doubled compared to the control group. This supports previous findings by [7] that the application of the transformer model in adaptive learning can strengthen personalization and improve learning retention. However, the score improvements may not solely be attributed to the adaptive system, but could also result from increased intrinsic motivation due to the novelty of the technology-based approach. This requires further investigation in long-term studies.

DeepSeek's ability to understand long contexts and sequence materials based on individual needs proved to be a key advantage. In addition, the integration of interaction logs and learning preferences allows the system to continuously adjust and recommend the most relevant material, approaching the principle of feedback loops-based learning. [4]. However, there are still some challenges, such as:

1. Dependence on the quality of interaction log data.
2. High model training time (though can be overcome with light fine-tuning).
3. System adaptation is still limited to text - need to explore multimodal (video/audio adaptive).

The use of AI technology not only accelerates administrative processes, but also improves the effectiveness of student learning, resulting in a more optimal educational experience thanks to the collaboration between technological innovation and teacher competence[18]. Thus, artificial intelligence serves as an enabler in providing a more meaningful learning experience, increasing learners' active participation, while optimizing learning outcomes. Not only enriching the quality of education, this adaptive system also opens wider opportunities for equal access to quality education[19]. These results confirm the potential of DeepSeek Transformer in digital learning optimization and provide a foundation for the development of more efficient adaptive systems to support contextual personalization of materials [20].

4. CONCLUSION

Based on the research results, adaptive modeling based on DeepSeek Transformer is proven effective in improving student learning outcomes in Information and Communication Technology subjects. This adaptive system is able to customize learning materials according to the needs and learning styles of individual learners, as indicated by a significant increase in post-test scores and active involvement in the learning process. In addition, students' perception of the system is very positive, both in terms of ease of understanding the material, suitability of needs, as well as visualization and navigation. Nevertheless, this study has limitations in terms of material coverage (text only), institutional scope, and relatively short evaluation period. Therefore, further research is recommended to develop a multimodal-based adaptive learning system and evaluate its impact in the long term and across educational institutions.

ACKNOWLEDGMENT

The authors would like to express their sincere gratitude to all parties who contributed to the completion of this study, including the participating students, teachers, and institutions that supported the research process.

REFERENCES

[1] L. Lukman, R. Agustina, and R. Aisy, “Problematika Penggunaan Artificial Intelligence (AI) untuk Pembelajaran di Kalangan Mahasiswa STIT Pemalang,” *Madaniyah*, vol. 13, no. 2, pp. 242–255, 2023. doi: 10.58410/madaniyah.v13i2.826

[2] A. Franz *et al.*, “Pelatihan Penerapan Artificial Intelligence (AI) untuk Menunjang Aktifitas Pembelajaran pada Sekolah Dasar Daarul Hijrah Al-Amin Samarinda,” *JLP : Jurnal Lentera Pengabdian*, Oct. 2023. doi: 10.59422/lp.v1i04.139

[3] K. S. Kartini and I. N. T. A. Putra, “Respon Siswa Terhadap Pengembangan Media Pembelajaran Interaktif Berbasis Android,” *Jurnal Pendidikan Kimia Indonesia*, vol. 4, pp. 12–19, 2020. doi: 10.23887/jpk.v4i1.24981

[4] E. Panadero and J. Alonso-Tapia, “How Do Students Self-Regulate? Review of Zimmerman‟s Cyclical Modelof Self-Regulated Learning,” *Anales de Psicologia*, vol. 30, no. 2, pp. 450–462, 2014. doi: 10.6018/analesps.30.2.167221

[5] A. Vaswani *et al.*, “Attention Is All You Need,” Conference on Neural Information Processing Systems, 2017. doi: 10.48550/arXiv.1706.03762

[6] C. Wang and M. Kantarcioglu, “A Review of DeepSeek Models’ Key Innovative Techniques,” *ArXiv*, Mar. 2025. doi: 10.48550/arXiv.2503.11486

[7] A. Paramythis and S. Loidl-Reisinger, “Adaptive Learning Environments and e-Learning Standards,” *IEEE Transactions on Learning Technologies*, 2023.

[8] N. Nurhayati, M. Suliyem, I. Hanafi, and T. T. D. Susanto, “Integrasi AI dalam collaborative learning untuk meningkatkan efektivitas pembelajaran,” *Academy of Education Journal*, vol. 15, no. 1, pp. 1063–1071, 2024. doi: 10.47200/aoej.v15i1.2372

[9] A. H. Kaluge, “Pemanfaatn AI Untuk Meningkatkan Pemahaman Konsep Matematika di Era Digital,” *SEMNAPTIKA IV*, 2024.

[10] F. Naseer and S. Khawaja, “Mitigating Conceptual Learning Gaps in Mixed-Ability Classrooms: A Learning Analytics-Based Evaluation of AI-Driven Adaptive Feedback for Struggling Learners,” *Applied Sciences*, vol. 15, no. 8, p. 4473, 2025. doi: 10.3390/app15084473

[11] Z. Qian *et al.*, “Harnessing the Power of Large Language Model for Uncertainty Aware Graph Processing,” *ArXiv*, Mar. 2024.

[12] I. Ghozali, “Aplikasi analisis multivariete dengan program IBM SPSS 23,” 2018.

[13] D. Eriawan and L. V. Putra, “Pengaruh Model Pembelajaran Savi Berbantuan

Cafas terhadap Pemahaman Konsep Siswa,” *JANACITTA : Journal of Primary and Children’s Education*, vol. 8, pp. 2615–6598, Mar. 2025. doi: 10.35473/janacitta.v8i1.3862

[14] E. Humolungo, G. Abdullah, and P. Fakultas Ilmu Pendidikan Univesitas Negeri Gorontalo, “Pengaruh Model Pembelajaran Inquiry Berbantuan Media Wordwall Terhadap Hasil Belajar Siswa Materi Wujud Zat dan Perubahan di Kelas IV SD,” *SCIENCE : Jurnal Inovasi Pendidikan Matematika dan IPA*, vol. 5, no. 2, 2025.

[15] X. Wang, Z. Chen, H. Wang, L. Hou U, Z. Li, and W. Guo, “Large language model enhanced knowledge representation learning: A survey,” *Data Sci Eng*, pp. 1–24, 2025. doi: 10.48550/arXiv.2407.00936

[16] P. P. Kuantitatif, “Metode Penelitian Kunatitatif Kualitatif dan R&D,” *Alfabeta, Bandung*, 2016.

[17] H. N. Boone Jr and D. A. Boone, “Analyzing likert data,” *The Journal of extension*, vol. 50, no. 2, p. 48, 2012. doi: 10.34068/joe.50.02.48

[18] N. Zebua, “Optimalisasi Potensi dan Pemanfaatan Artificial Intelligence (AI) Dalam Mendukung Pembelajaran di Era Society 5.0,” *Pentagon : Jurnal Matematika dan Ilmu Pengetahuan Alam*, vol. 2, no. 4, pp. 185–195, Dec. 2024. doi: 10.62383/pentagon.v2i4.314

[19] Supriyatmoko, K. Anam, and W. Kurniawan, “Model Pembelajaran Adaptif Berbasis Kecerdasan Buatan: Peluang Dan Tantangan Dalam Mewujudkan Pendidikan Personalisasi,” *STRATEGY : Jurnal Inovasi Strategi dan Model Pembelajaran*, Jan. 2025. doi: 10.51878/strategi.v5i1.4944

[20] I. N. T. A. Putra, A. Yuniarti, H. Fabroyir, and I. P. B. G. P. Raharja, “Transformer Performance Evaluation in 3D Reconstruction of Balinese Mask Wood Carving,” in *2024 International Seminar on Intelligent Technology and Its Applications (ISITIA)*, 2024, pp. 285–289.