

AI-Integrated Personalized Learning for High School Students

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Abstract

The 2018 General Education Program in Vietnam emphasizes personalized learning and the application of technology in teaching. This study proposes a customized learning system integrating artificial intelligence (AI) to optimize the learning experience for high school students. The system is designed according to the Client-Server model, including LMS, AI Engine, and learning database. The research method focuses on developing Machine Learning algorithms, precisely the K-Nearest Neighbors (KNN) algorithm, to predict learning outcomes, applying Adaptive Learning to suggest appropriate content, and integrating AI chatbots to support students. In addition, the system also applies facial recognition to take attendance and monitor learning behavior. The research results show that the system helps students have a flexible learning path, increases interaction, and supports teachers to monitor learning progress more efficiently. This model could expand to other levels of education and contribute to promoting digital transformation in education.

Keywords

Personalized Learning, Artificial Intelligence in Education, Learning Management Systems (LMS), Blended Learning, Learning Progression

1. Introduction

In modern education, personalized learning has become an important trend to meet students' diverse needs and abilities. The 2018 General Education Program in Vietnam aims to innovate teaching methods towards developing individual capacity, encouraging the application of digital technology in teaching and learning. However, traditional teaching methods have not effectively exploited technology to support personalizing the learning path [1]. According to research by [2],

teachers have not yet effectively exploited artificial intelligence in education, although this technology has great potential in personalizing teaching content.

Current learning management systems (LMS) such as Moodle and Canvas mainly focus on content management and learning progress tracking. They are not yet able to flexibly adjust to the needs of individual students [3]. Artificial intelligence (AI) opens great potential for analyzing learning data, predicting outcomes, and automatically adjusting appropriate learning content [4]. According to research by [5], AI can help the education system shift from the traditional teaching model to personalizing the learning path, helping to improve learners' knowledge acquisition efficiency.

The study aims to develop a personalized learning system that integrates AI, designs an innovative LMS that can adjust content according to individual abilities, helps adjust learning content according to student abilities, and supports teachers in managing the learning process effectively. From there, propose a personalized learning model that combines Blended Learning and AI, helping to build an automatic learning path according to each student's ability. According to [6] [7], learning data analysis combined with an adaptive learning model can improve knowledge acquisition and adjust content to suit everyone. The system uses Adaptive Learning through Machine Learning algorithms to suggest appropriate content while supporting teachers in managing the learning process, contributing to improving teaching effectiveness [8] [9] also emphasized that the use of Learning Analytics and AI can provide important information about students' learning behavior, helping to personalize the learning experience more effectively.

Predictive maintenance in industrial systems has been significantly improved through the integration of non-destructive testing techniques. Recent advancements, such as terahertz technology, have provided innovative solutions for material inspection and defect detection [10]. Recent studies have integrated autonomous inspection systems, such as terahertz-based dynamic line-scan approaches, for enhanced defect identification [11].

2. Materials and Methods

2.1. Concept of Personalized Learning

Personalized learning is an educational approach that tailors learning to each student's strengths, needs, skills, and interests [12] [13]. Each student receives a learning plan based on their knowledge and best learning style [14]-[16]. According to Williams and Brown (2024) [17], personalized learning can be supported by intelligent learning systems that use artificial intelligence to tailor content to everyone.

Personalized learning systems often apply digital technology, especially artificial intelligence (AI) and machine learning, to analyze learning data, predict outcomes, and provide appropriate learning paths [18]. Khanal *et al.*, (2024) [19] pointed out that the application of AI in adaptive learning systems enhances students' learning ability and supports teachers in monitoring learning progress. Ac-

According to Miller & Thompson's (2024) [20] research, AI in education helps automate the teaching process and improves learning performance through personalized algorithms.

This model helps students acquire knowledge more effectively and helps teachers monitor individual progress and adjust teaching methods accordingly [21]. Clark and Zhang (2024) [22] emphasize that integrating AI into personalized learning can create flexible learning experiences, helping students develop according to their abilities and needs.

2.2. AI Applications in Personalized Learning

Adaptive Learning is a method that uses artificial intelligence to adapt learning content to each student's ability. This technology analyzes learning data, identifies strengths and weaknesses, and recommends personalized learning paths [23]. Compared to traditional methods, Adaptive Learning helps students access content at their own pace, avoiding learning too fast or too slow [12]. According to research by [24], adaptive learning technologies, combined with personalized feedback and interactive AI tools, positively impact student engagement, mainly when supported by digital skills. AI systems can predict difficulties students may encounter and automatically provide supplementary materials, helping to improve learning performance, while teachers have additional tools to manage their classrooms more effectively.

Machine Learning is a technology that enables personalized learning systems by predicting learning outcomes and suggesting appropriate pathways. Algorithms such as K-nearest neighbors (KNN), Random Forest, and Long Short-Term Memory (LSTM) can analyze student data, identify learning patterns, and make more accurate predictions over time [25]. The system can alert teachers to students at risk of learning poorly, thereby adjusting teaching methods [19]. At the same time, AI suggests appropriate content, helping students access knowledge correctly. Integrating AI into adaptive learning enhances personalization and improves teaching efficiency through intelligent algorithms [23].

AI Chatbot: Thanks to Natural Language Processing (NLP) technology, chatbots can flexibly understand and respond to questions, providing relevant information or suggesting reference materials. Students can use chatbots like ChatGPT to learn complex content, review knowledge, or do exercises without waiting for teachers. In addition, chatbots also support teachers by reducing the burden of answering repetitive questions, helping them focus more on teaching. Thanks to personalization, AI chatbots can adapt to each student, helping to improve the learning experience and increase the efficiency of knowledge acquisition. According to research by [26], learning support chatbots can improve learning performance and increase student motivation. In addition, research by [27] shows that chatbots can provide instant feedback and support students in solving complex problems. Recently, research by [28] explored the use of AI chatbots in education and found that they can be crucial in supporting personalized learning.

3. Results Discussion

The proposed predictive maintenance model demonstrates high accuracy in forecasting machine failures, minimizing unexpected downtime. However, alternative approaches, such as real-time non-destructive evaluation, offer a different perspective by detecting material degradation rather than predicting failures in advance.

While predictive models based on neural networks provide significant advantages in forecasting failures, non-destructive evaluation techniques, such as terahertz-based inspections, have also been explored as alternative solutions [10] [11].

Future research could explore hybrid approaches integrating predictive analytics with non-destructive testing for a more comprehensive maintenance strategy.

3.1. System architecture

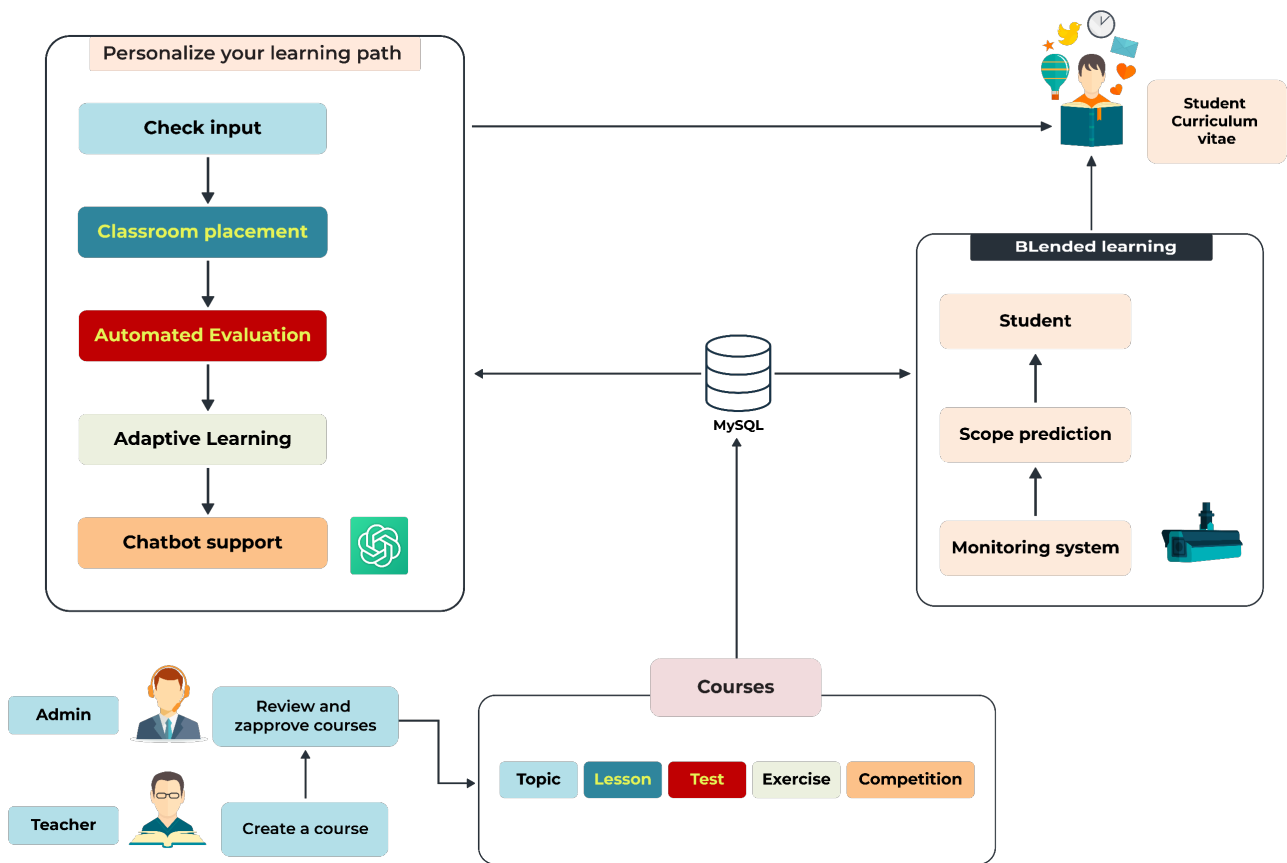


Figure 1. Alearning system diagram.

The model (Figure 1) in the above image depicts an intelligent learning system that combines AI and blended learning. The system personalizes learning paths by checking input, placing classes, automatic assessment, adaptive learning, and chatbot support. Learning data is stored and connected to the system to predict learning ranges and monitor students. The system also allows teachers to create

courses and administrators to approve and manage content such as lessons, tests, assignments, and competitions. This model helps improve teaching quality and optimize students' learning experience.

3.2. Basic Functions and Authorizations of the Learning Management System

The research team has experienced popular learning systems today, such as Moodle Canvas, ... to build an integrated Blended Learning system, the team analyzed and proposed the essential functions and subjects in the system as follows (Figure 2).

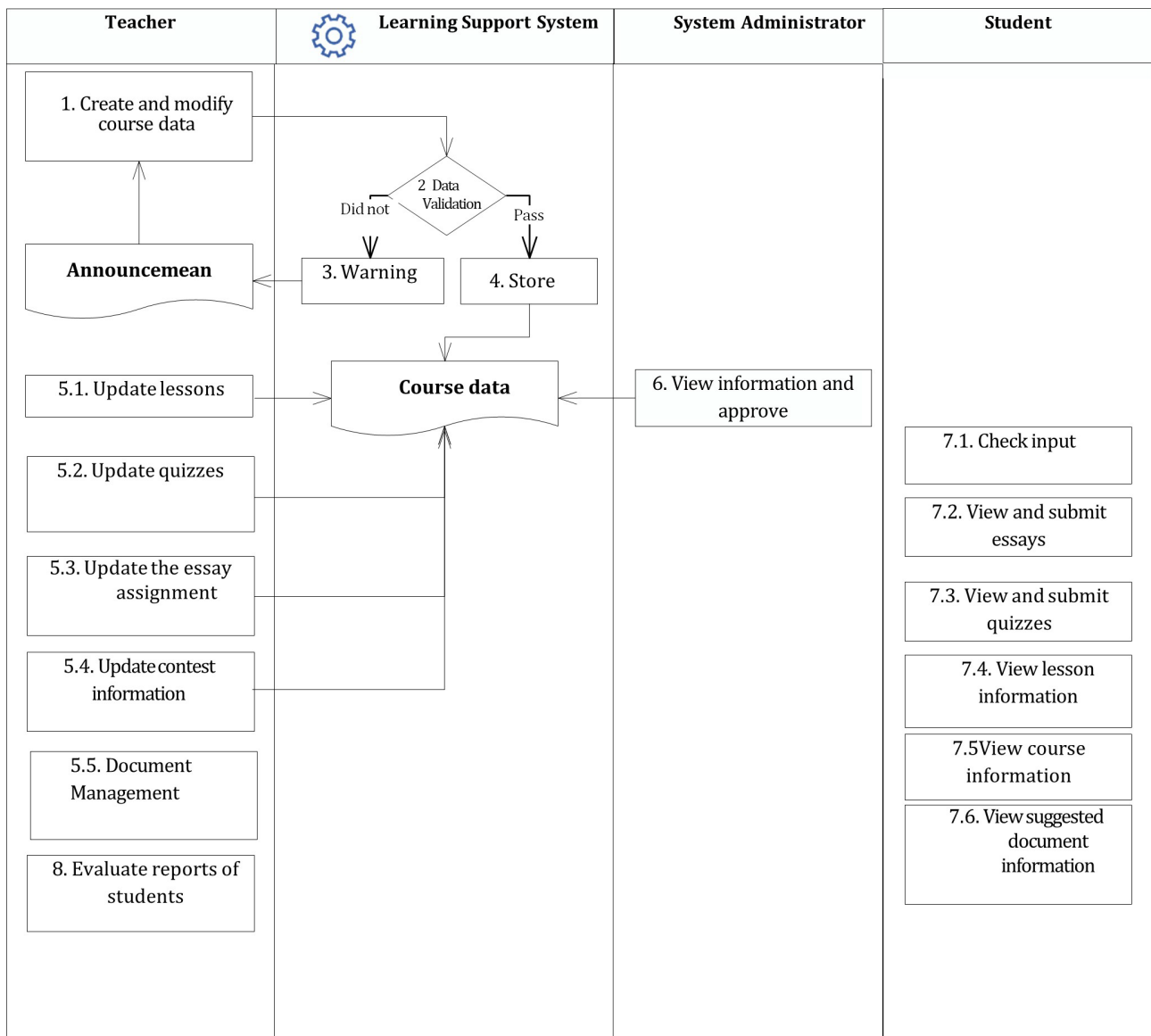


Figure 2. Decentralization in the system.

Courses are created by teachers on the system and their content is checked by subject group leaders (admins) before being displayed on the system.

To ensure the effective operation of the AI-integrated personalized learning system, the research team has evaluated and analyzed existing learning management systems (LMS) such as Moodle and Canvas. Based on these analyses, we have designed a learning system that includes essential functions while also providing a flexible decentralization mechanism for managing learning activities.

1) Administrators (Admin): Manage the entire system, ensuring smooth operation, setting learning pathways, managing access permissions, and approving content uploaded by teachers. Before a course is displayed on the system, it must be approved by subject group leaders.

2) Teachers: Create and manage course content, including lecture materials, quizzes, assignments, and assessments. They also track students' progress and adjust learning paths based on AI recommendations.

3) AI Engine: This component analyzes student progress, provides adaptive learning recommendations, predicts learning outcomes, and offers personalized feedback based on machine learning models such as K-Nearest Neighbors (KNN) and Random Forest.

4) Students: Access personalized learning content, exercises, and assessments. The AI system continuously monitors student progress and adjusts content difficulty levels accordingly.

5) Parents: Monitor their child's academic progress through a dedicated dashboard that provides insights into learning trends and personalized recommendations.

6) Learning Analytics Dashboard: Provides detailed reports on learning progress, enabling teachers and students to make data-driven adjustments to learning strategies.

7) Chatbot Support System: Integrated with GPT-4, the chatbot assists students by answering questions related to course content, suggesting additional learning materials, and providing real-time feedback on assignments.

3.3. Technology Selection

The research team uses the Laravel Framework with PHP programming language due to its security and compatibility with the MVC model. At the same time, ReactJS supports flexible UI and MySQL databases to meet large data storage requirements.

3.4. User Interface (UI) Design

The research team's requirements are a user-friendly interface and transparent colors. From there, the research team researched and built the user interface of the learning system as follows (**Figure 3**, **Figure 4**).

3.5. Results of Designing an AI-Integrated Personalized Learning System

The system is designed on the web with the domain page with the address <https://ailaarninglqd.com/>.

USER INTERFACE

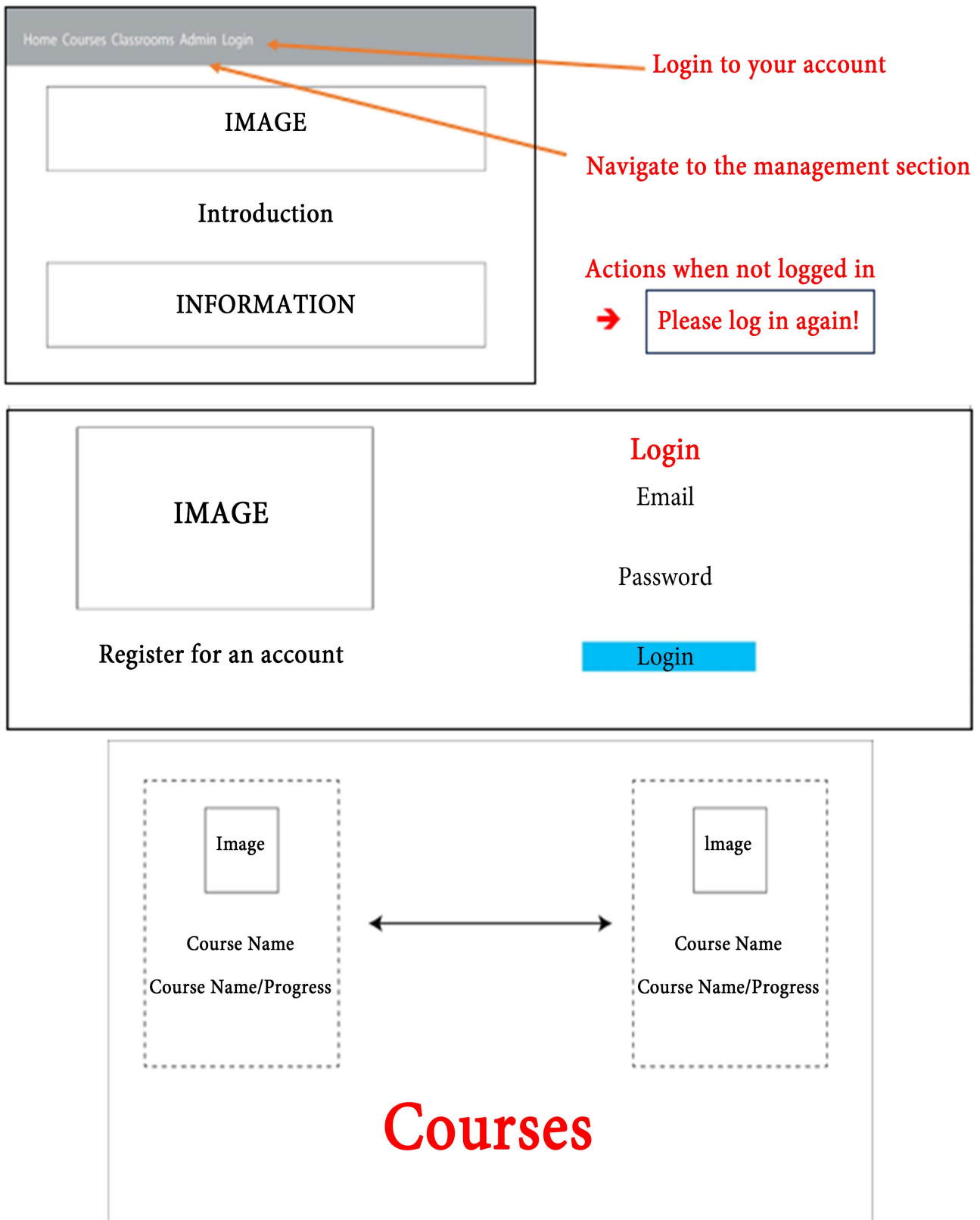
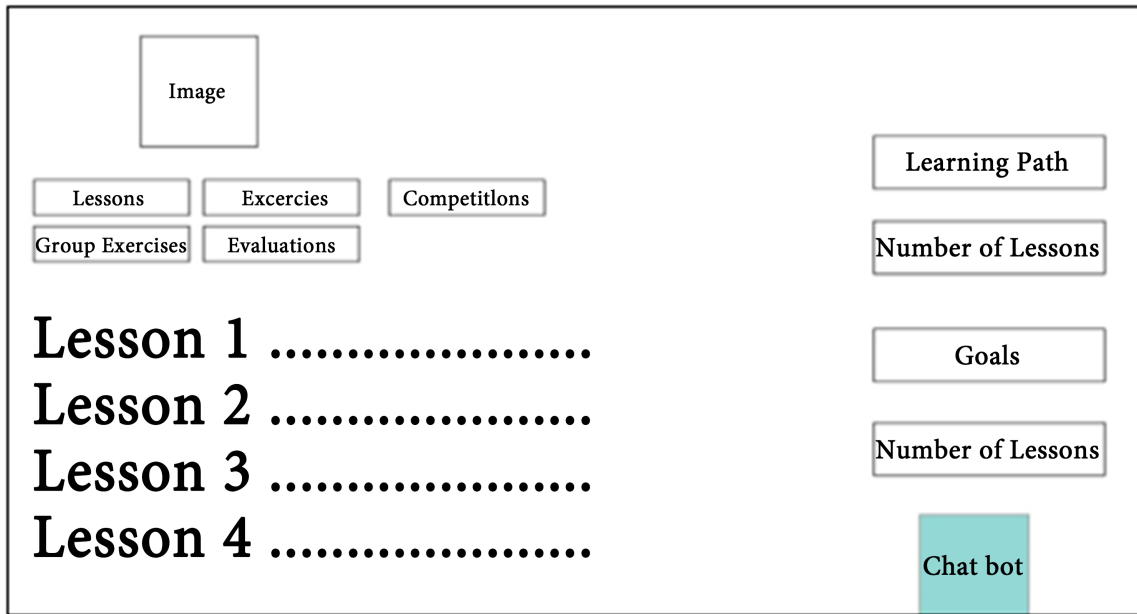
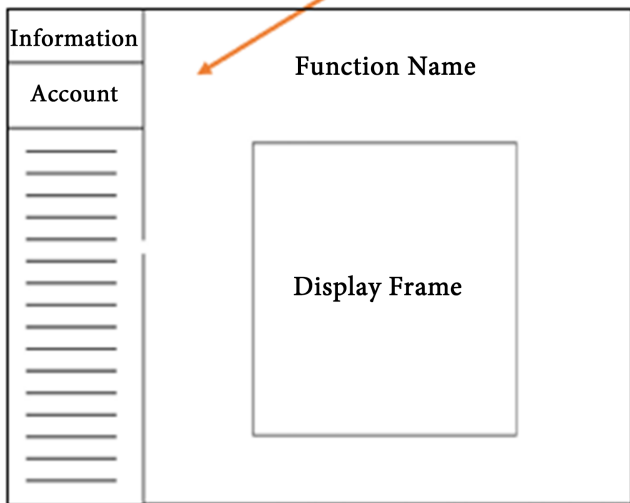


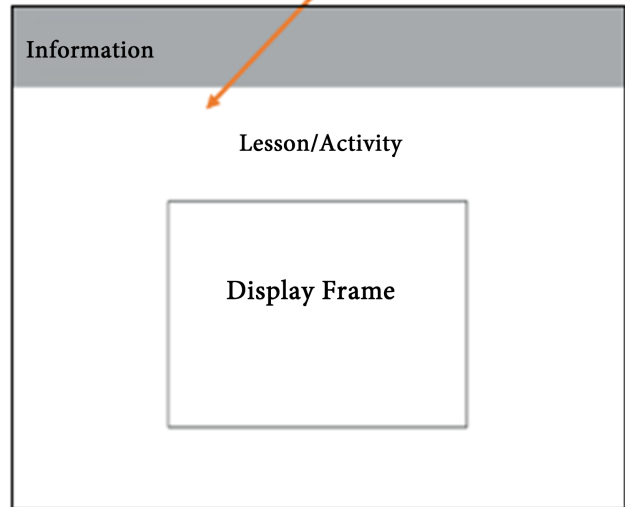
Figure 3. Rough sketch of the user interface—Courses.



Admin Interface



Lessons, Exercises Interface



Requirements:

Web interface, Vietnamese font Unicode TCVN 2001: 6909

Build based on a 3-layer model

Final interface of the website

Use appropriate colors and images

Example: Blue for lessons; Red for main sections

Figure 4. Rough sketch of the user interface—**Lessons.**

Some functions in the personalized learning system, such as **Figure 5**, **Figure 6** and **Figure 7**.

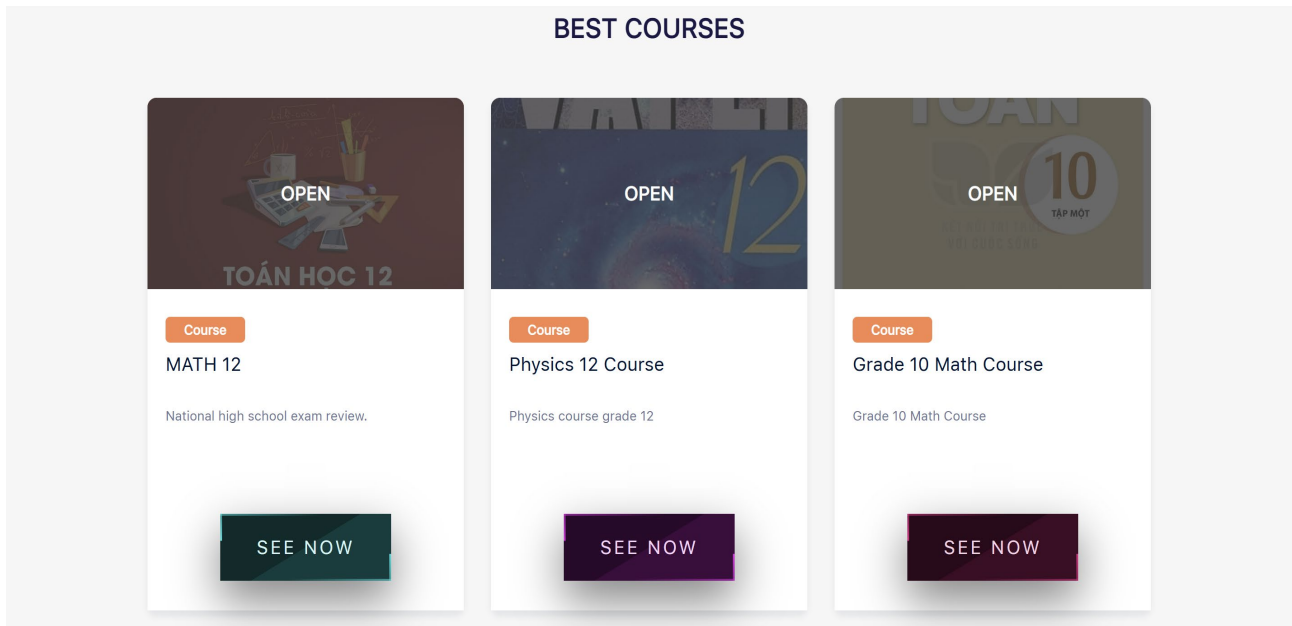


Figure 5. Homepage interface of courses.

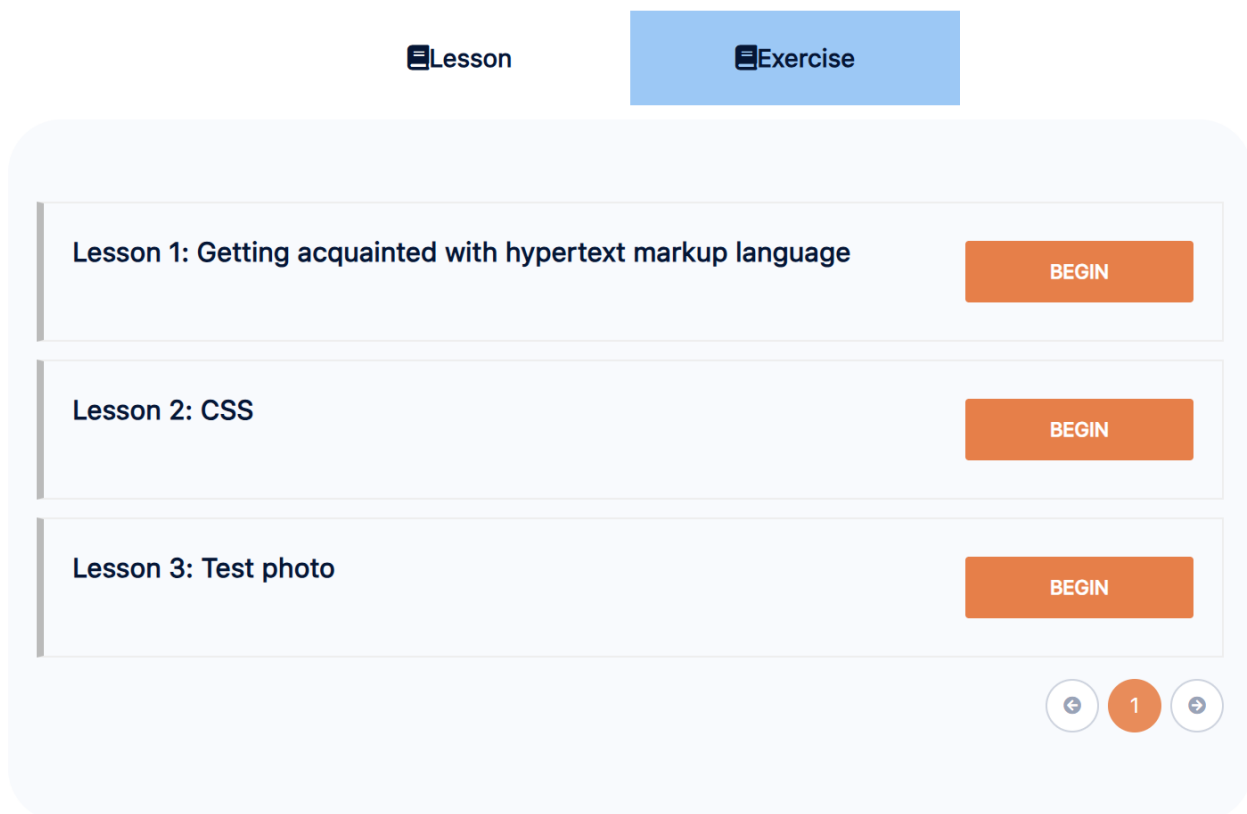


Figure 6. Interface of lessons and exercises in the course.

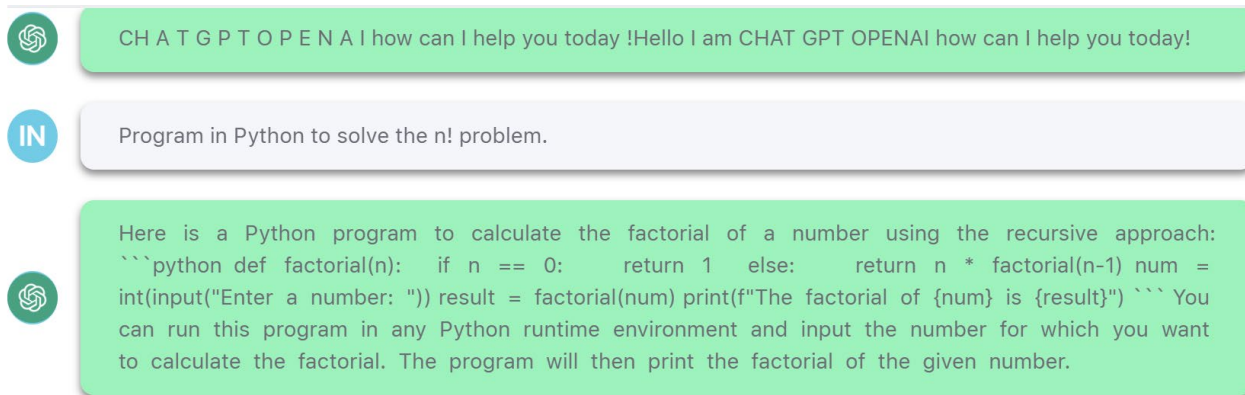


Figure 7. The Chatbot function interface of ChatGPT is integrated.

3.6. Approaches to Personalizing the Learning Process

3.6.1. Approach 1: Personalized Learning Pathway System Automated Class Placement Process for Students (Figure 8)

Each course will have classes from weak to good, each with a standard score. If a student has a higher average score, he/she will be transferred to another class. Teachers can also create separate classes to monitor students.

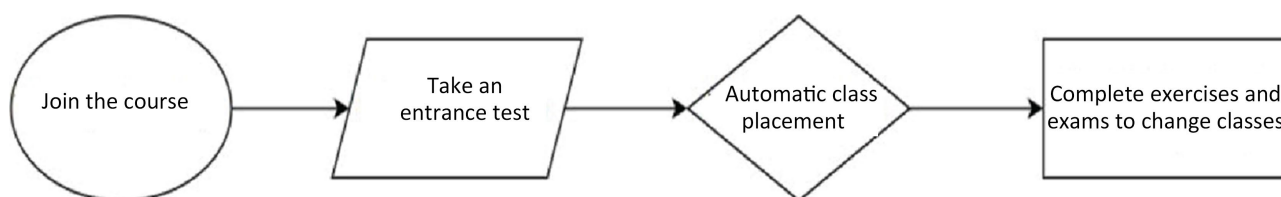


Figure 8. Automatic layering process.

Build an automatic suggested learning path according to the responsive learning model (Table 1).

Teachers will evaluate the exercises according to four levels, from easy to super difficult. Based on the number of difficult exercises for each topic and the level of completion of the lessons for each topic by the student, the system will provide a suitable learning path, not following a certain path.

Table 1. Suggested automatic learning paths.

Topic	Lessons Completed	Number of Difficult and Very Difficult Lessons	Suggested Study Order
Trigonometry	6/10 lessons = 0.6	7 difficult and very difficult lessons	Study first
Sequences	4/8 lessons = 0.5	9 difficult and very difficult lessons	Study third
Statistics	3/5 lessons = 0.5	5 difficult and very difficult lessons	Study second

The research team also used the adaptive learning model, in which the teacher grades the assignments, and only when the student achieves a total score higher than the standard score will they be allowed to do more advanced tasks. The number of assignments submitted is also limited, helping to ensure that students'

scores accurately assess their abilities. According to Chan (2023) [29] study, adaptive learning can improve learning performance and increase student motivation. In addition, Hill *et al.*, (2023) [27] study found that using automated assessment tools in adaptive learning helps provide immediate feedback and supports students in solving complex problems. Recently, Chen and L. J. Duh (2020) [30] study explored the use of responsive learning models in education and found that they can be crucial in supporting personalized learning (Figure 9).

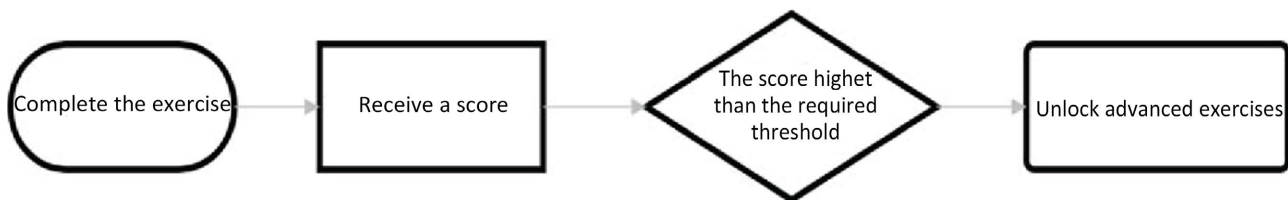


Figure 9. Exercise unlocking process.

Automatic assessment comment model

The research team believes that students should receive different assessments for each score to personalize the learning process. From there, we have the problem of classifying the scores corresponding to the comments with two suitable machine learning algorithms: KNN (K-Nearest Neighbors) and SVM (Support Vector Machine—Table 2).

Table 2. Comparison of KNN and SVC algorithms.

Criteria	KNN	SVM
Operation	Based on the nearest neighbors	Finds the optimal hyper-plane
Advantages	Fast, easy to implement	Suitable for nonlinear data
Disadvantages	Slow computation with large datasets	Resource-intensive, complex

Based on the comparison, the group found that using the KNN algorithm would be more straightforward and suitable for the problem's data and information requirements.

The KNN algorithm represents points and evaluations on a two-dimensional space, with the x-axis containing points representing the number of points and the y-axis representing the most significant deviation in the score data set.

Using the formula to calculate the distance between points:

$$\text{distance} = \sqrt{(x1 - x2)^2 + (y1 - y2)^2 + (z1 - z2)^2 + \dots} \quad (1)$$

The algorithm will receive k points closest to the input data, from which the system will give an assessment based on the received score. Testing the KNN machine learning algorithm above, with an input data set of more than 100 data, the test data set shows that the output result with $K = 2$ is the most accurate; choose $K = 2$.

At the same time, the system also suggests exercises with a suitable level of dif-

faculty that have not been done, documents to read related to exercises that have been done incorrectly, and chapters to study more.

Chatbot supports students

The system is integrated with the GPT-4 chatbot to help students answer questions. In addition, questions and answers will also be saved as pairs (input, output) in the system to help teachers check if they suspect students are using chatbots to cheat in studying or testing.

3.6.2. Approach 2: Personalizing the Learning Process Using the Blended Learning Method

Model for monitoring students' learning process

The research team also developed functions for monitoring students during the direct learning process. The attendance system uses face recognition and OpenCV libraries to recognize faces for attendance. To monitor behaviors such as falling asleep, using phones, and talking, the research team compared the YOLOv8, CNN, and Faster R-CNN models based on the criteria: Accuracy (A), Recall (R), Precision (P), and F1-Score on the same test set. According to the study of [31], applying the YOLOv8 model in student behavior recognition shows high accuracy and fast processing time. In addition, the study by [32] showed that the use of the Faster R-CNN model significantly improved the performance of classroom behavior monitoring. Furthermore, the study by [31] compared the performance of YOLOv8, CNN, and Faster R-CNN models in student behavior monitoring, showing that YOLOv8 was superior in terms of accuracy and processing speed.

Table 3. Comparison of monitoring models.

Model	A	R	P	F1 - Score	Total score
YOLOv8	90.0%	8.05%	88.0%	86.5%	87.1%
CNN	80.0%	70.0%	75.0%	72.5%	74.1%
Faster R-CNN	85.0%	80.0%	82.0%	81.0%	82.0%

The research team used the Yolov8 model pre-trained with the large COCO and ImageNet datasets. To identify cases with signs of phone use, falling asleep, and talking, the team refined and continued to train the model with a dataset of more than 8,000 images (**Table 3**).

1) Building a score prediction model based on learning data

The research team proposed predicting the first semester scores of 12th-grade students to help parents or students grasp their abilities and better prepare for important exams.

The input data includes semester scores from semester 1 of grade 10 to semester 2 of grade 11 (a total of 4 semesters) of 10 subjects from 1,000 students collected from the education management system. To ensure consistency and reduce noise, the research team applied the StandardScaler normalization method (mean=0, std=1) to balance subjects' contributions with different scales. The data after normalization was divided into an 80:20 ratio.

2) Building a machine learning algorithm model to predict scores

The research team used two main algorithms: Gradient Boosting Regressor (GBR) and Random Forest Regressor (RFR). GBR can handle nonlinear data and improve accuracy by combining multiple weak decision trees, while RFR takes advantage of bagging techniques to reduce variance, suitable for noisy data. To optimize the results, the team used Voting Regressor to combine the outputs of GBR and RFR, taking advantage of the advantages of both methods. According to the study of [14], combining regression models through Voting Regressor helps improve the accuracy of predicting students' scores. In addition, Johnson and Lee (2023) [15] showed that using GBR and RFR in predicting learning outcomes gives higher performance than single models. Furthermore, Kim & Park (2023) [33] demonstrated that applying a Voting Regressor combining GBR and RFR helps to reduce prediction error and enhance model reliability.

3) Building an LSTM model to predict scores

The team tested the hypothesis of time dependence between semesters using the Long Short-Term Memory (LSTM) model. The data was reformatted into a 3D tensor [2000, 4, 10], corresponding to four semesters and ten subjects. The model structure includes the first LSTM layer (64 units, `return_sequences=True`) to analyze short-term relationships and the Dropout layer (0.2) to reduce overfitting. The second LSTM layer (32 units) aggregates information. The output dense layer (10 units) predicts the scores of ten subjects.

Training results (Table 4)

Mean Absolute Error (MAE), Root Mean Squared Error (RMSE), and R^2 (Coefficient of determination) are used to evaluate the performance of the two models above.

Table 4. Comparison of two score prediction models.

Scale	Voting Regressor	LSTM
MAE (\pm)	0.35 \pm 0.01	0.48 \pm 0.02
RMSE (\pm)	0.49 \pm 0.02	0.65 \pm 0.03
R^2 (\pm)	0.91 \pm 0.01	0.79 \pm 0.01
Training time	18 minutes	3 hours 10 minutes

The results show that Voting Regressor outperforms with a lower MAE (0.35) and a higher R^2 (0.91), reflecting a more accurate prediction. This difference may be due to the nonlinear nature of the data, which is suitable for the ensemble method. Therefore, the research team decided to use Voting Regressor as the primary method for the problem.

Building a learning outcome report building a learning outcome report

With the input of academic scores by subject and semester, extracurricular activities (roles, achievements), teacher comments, and career goals, the research team applied a hierarchical model and inference chain to process and build prompts for Large Language Models (LLM), specifically ChatGPT-4. Ac-

According to the study by [34], the use of hierarchical models in natural language processing helps improve the accuracy and efficiency of creating personalized learning reports. Additionally, Smith & Lee (2023) [14] showed that chained reasoning combined with LLM can enhance contextual understanding and generate content that is relevant to individual students. Recently, Johnson and Wang (2024) [16] explored the integration of ChatGPT-4 in education and found that the use of well-designed prompts can significantly improve the quality of learning reports.

Layer 1: Objective Analysis

Calculate the academic slope (Δ) to determine the trend of scores:

$$\Delta = \frac{y_k - y_{k-1}}{x_k - x_{k-1}} \quad (2)$$

Where x_k is the semester order, and y_k is the score for semester k .

Output: Trend of subject scores and strengths/weaknesses during the study process.

Layer 2: Simple Context Analysis

Evaluate the relevance of extracurricular activities to career goals. Sample prompt: "Is the activity [participating in the Science Club] relevant to the goal [software engineer]? Briefly explain."

Layer 3: Strengths and Weaknesses Analysis

Analyze comments and extract strengths (e.g., Creativity, perseverance) and weaknesses (e.g., Impatience). Sample prompt: "From the comment [Need to improve writing skills], analyze strengths and weaknesses and suggest ways to improve." Output: suggestions for development.

During the analysis, actions will be performed according to the Chain-of-Thought Reasoning, including:

Step 1. Observation: Extract information from input data. For example: "Math score increased from 7.0 \rightarrow 9.2, join Science club."

Step 2. Intermediate analysis: Combine results from layers. For example: "Positive trend in Math ($\Delta = +0.8$), Science club is suitable for engineering goals."

Step 3. Conclusion: Recommend actions based on analysis. For example: "Keep studying advanced Math, take more programming courses."

The report provides a graph of grades, progress comments, progress and decline in subjects, teacher comments, extracurricular achievements, strengths/weaknesses, and suggestions for development to achieve career goals (**Figure 10**).

4. Conclusions

Enhancing security features and ensuring user privacy can also improve the system, helping to build a safe, modern learning environment that is in line with the digital transformation trend in education.

The AI-integrated personalized learning system proposed in this study aims to address the need for customized learning paths in alignment with the 2018 General

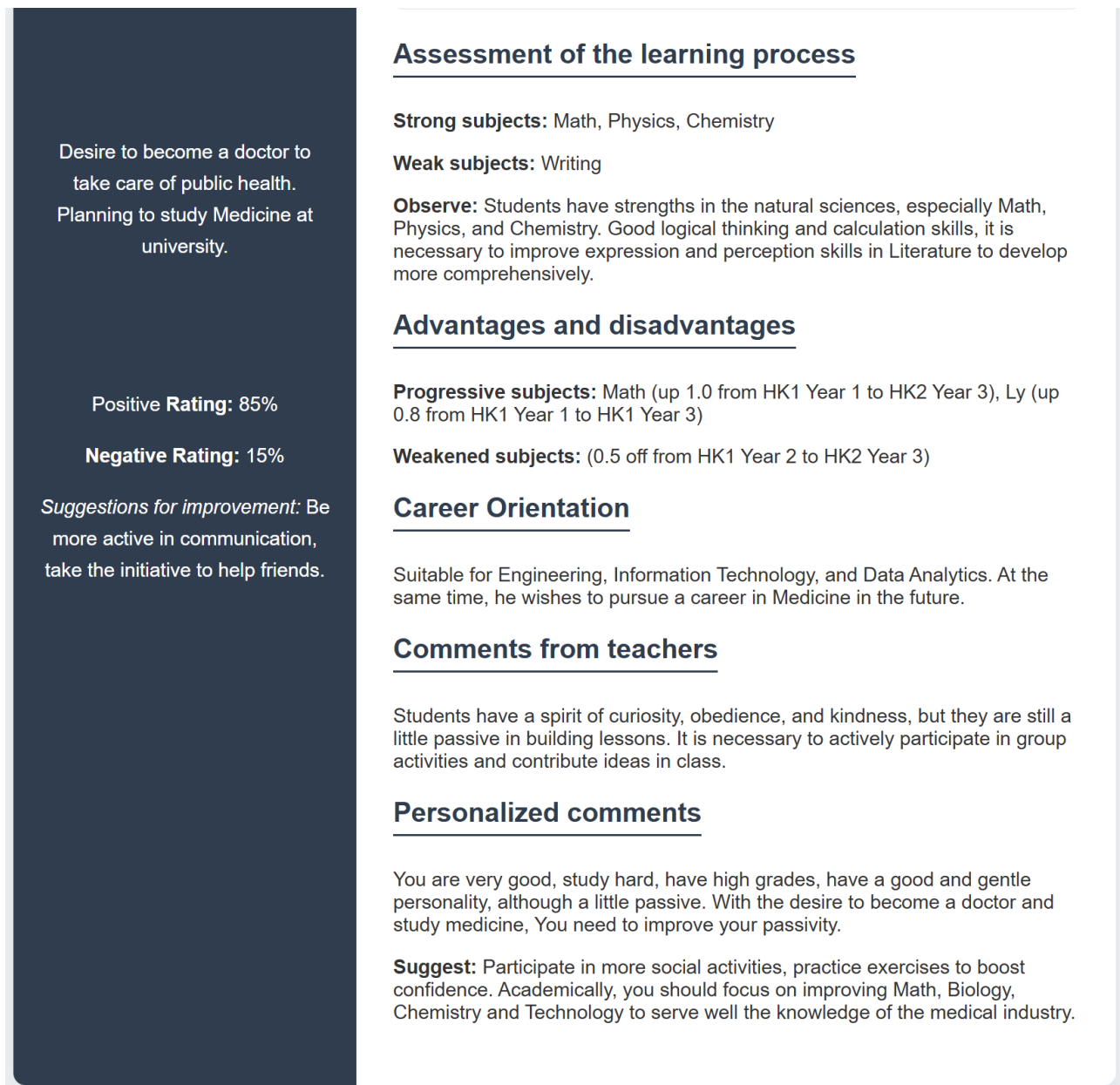


Figure 10. Example of score comments and career guidance.

Education Program in Vietnam. By leveraging AI and Machine Learning, the system dynamically adapts learning content based on students' individual abilities, predicts learning outcomes, and enhances teacher-student interaction. The research findings demonstrate that AI-driven personalization improves learning flexibility, optimizes content delivery, and enhances student engagement. Additionally, the implementation of facial recognition contributes to efficient classroom management and attendance tracking, reinforcing the importance of AI in educational administration.

The research results show that the system brings many benefits, including increasing flexibility in learning paths, improving interaction between students and

teaching content, and supporting teachers in monitoring learning progress. In addition, the facial recognition feature helps improve the efficiency of classroom management, creating a more effective and transparent learning environment. St-Hilaire *et al.*, (2022) [35] pointed out that intelligent tutoring systems can significantly improve online learning outcomes for millions of learners. This system has the potential to expand to other levels of education and contributes to promoting the digital transformation process in education. In the future, personalized learning systems integrated with AI will continue to be researched and developed to improve the effectiveness of supporting students and teachers. One of the critical expansion directions is to optimize Machine Learning algorithms, adding the ability to analyze real-time learning data to predict the learning progress of each student more accurately each student's learning progress. Laak and Aru (2024) [36] emphasize combining AI and personalized learning to achieve modern educational goals.

In addition, integrating more advanced technologies, such as Generative AI, to personalize further learning content and develop more innovative AI chatbots to support students in the self-learning process will make the system more flexible and effective. In addition, expanding the scope of application to other levels of education and practical implementation in various educational environments will be essential steps to evaluate the system's applicability. Baillifard *et al.*, (2023) [37] conducted a case study on implementing learning principles with a personal AI tutor, demonstrating the potential of AI in supporting personalized learning.

Enhancing security features and ensuring user privacy can also improve the system, helping to build a safe, modern learning environment that is in line with the digital transformation trend in education. McLaren *et al.*, (2021) [34] discussed sharing student learning models between learning systems to improve the learning experience.

Practical Applications

This research has practical implications beyond theoretical contributions. The AI-powered adaptive learning system can be implemented in various educational environments, including K-12 education, vocational training, and higher education. In particular:

- **K-12 Education:** The system enables differentiated instruction, ensuring that students receive content tailored to their cognitive levels, which can bridge learning gaps and improve overall comprehension [2].
- **Higher Education:** Universities can utilize AI-integrated platforms to provide personalized learning paths for students in large-scale courses, fostering self-paced and competency-based learning models.
- **Corporate Training:** The adaptive learning model can be applied to professional development programs, helping employees acquire new skills in a structured and data-driven manner [1].
- **Remote and Blended Learning:** The AI-driven chatbot and automated assessment features provide continuous feedback and support, making remote edu-

cation more interactive and effective [38].

Future Work

While the system demonstrates promising results, several aspects require further development and validation. Future research will focus on:

- 1) **Enhancing AI Algorithms:** Improving predictive accuracy by integrating advanced deep learning models such as Transformer-based architectures.
- 2) **Expanding AI Chatbot Capabilities:** Developing AI-powered chatbots with enhanced Natural Language Processing (NLP) to provide contextualized learning assistance.
- 3) **Integration with Emerging Technologies:** Incorporating Augmented Reality (AR) and Virtual Reality (VR) for immersive learning experiences.
- 4) **Cross-Cultural Adaptation:** Expanding the system's applicability by tailoring content to diverse linguistic and cultural contexts to support international students.
- 5) **Scalability and Deployment:** Conducting large-scale pilot implementations in multiple educational institutions to assess the system's adaptability and effectiveness across different curricula.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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