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The Effect of a Diagnostic System for Scientific Competency Combined with a Personalized Intelligent Tutoring Module through Machine Learning for Enhancing the Learning Progression of Seventh Grade Students

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Abstract

This study investigated the effects of a diagnostic system for scientific competency, combined with a personalized intelligent tutoring module that utilized machine learning, on the learning progression of seventh-grade students. The study employed a decision tree algorithm in Python to analyze secondary data from 847 students. The decision tree algorithm was used to create a predictive model that could diagnose individual scientific competency levels, which informed the development of individualized learning pathways. The experimental study involved 176 students, who were divided into two groups: an experimental group that received interactive feedback and a control group that did not receive any feedback. The study utilized a one-way MANOVA to evaluate three dimensions of scientific competency: Explanation of Scientific Phenomena, Evaluation and Design of Scientific Inquiry, and Interpretation of Data and Use of Evidence. The findings demonstrated significant improvements in the experimental group across all dimensions, highlighting the importance of immediate feedback in enhancing comprehension and motivation. The system was also highly rated for its quality and user satisfaction. This study emphasizes the potential of intelligent tutoring systems to improve scientific competency and suggests further educational applications.

Keywords: *Multidimensional Competencies, Machine Learning, Intelligent Tutoring Module, Learning Progression*

INTRODUCTION

Amidst a time characterized by swift technological progress and complex global issues, education serves as a fundamental pillar for cultivating the necessary abilities to navigate the demands of the 21st century. Science education is essential for providing pupils with the necessary information and problem-solving skills to tackle intricate problems. The proper diagnosis of students' scientific competency is crucial in this educational endeavor. It forms the basis for customized instructional strategies and effective learning progressions. Studies demonstrate that adaptive learning systems, which tailor instruction to suit the specific needs of each student, have a substantial positive impact on educational results (Van Vaerenbergh & Pérez-Suay, 2021). These systems employ cutting-edge technology like machine learning (ML) and intelligent tutoring systems (ITS) to offer immediate, practical feedback, guaranteeing that education consistently matches students' developing skills (Bernacki, Greene, & Lobczowski, 2021).

The diagnosis of students' scientific competency continues to be a significant concern in Thailand, as educational achievements in science are behind global benchmarks. According to the PISA 2018 findings, Thai students had an average science score of 426, which was considerably lower than the OECD average of 489 (National PISA Center, Institute for the Promotion of Teaching Science and Technology, 2021). This disparity emphasizes the pressing necessity for inventive methods to augment scientific proficiency among students. Research has demonstrated that the combination of Intelligent Tutoring Systems (ITS) and Machine Learning (ML) can result in notable enhancements in student achievement. This is achieved by the provision of individualized feedback and the customization of learning routes to cater to individual needs (Tetzlaff, Schmiedek, & Brod, 2020).

The present state of education in Thailand reveals a notable deficiency in students' scientific proficiency, which reflects larger systemic difficulties. Conventional diagnostic approaches frequently do not offer prompt,

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practical feedback that is essential for making fast adjustments in real-time learning. In addition, current technologies fail to fully use technological developments, such as machine learning (ML) and intelligent tutoring systems (ITS), which have demonstrated promise in educational environments. Utilizing dynamic evaluation and adaptation is essential for ensuring consistent educational outcomes and effectively addressing individual learning needs (Richard et al., 2023).

Although there have been multiple attempts to incorporate technology into education, there is still a lack of study that particularly investigates the combination of machine learning (ML) with intelligent tutoring systems (ITS) to improve scientific proficiency in seventh-grade students. Prior research has examined digital evaluation instruments (Intasoi et al., 2020) but has not adequately tackled the requirement for prompt feedback and customized learning paths that cater to the unique demands of each student. Further work is required to explore how these technologies might be combined to develop a reliable diagnostic system. Moreover, there is a scarcity of research on the precise effects of adaptive learning systems on various components of scientific competence, such as the ability to explain scientific phenomena (ES), interpret data and utilize evidence (IE), and evaluate and design scientific inquiries (ED) (Anohina, 2007).

The motivation for this study is based on both theoretical and practical factors. Integrating machine learning (ML) and intelligent tutoring systems (ITS) has the potential to create accurate and adaptable diagnostic tools that can meet the various learning requirements. The research conducted by Jordan and Mitchell (2015) emphasizes the potential of machine learning to analyze intricate datasets and generate precise predictive models. Intelligent Tutoring Systems (ITS), as mentioned by Conati (2009) and Stankov et al. (2008), play a crucial role in delivering customized learning experiences and prompt feedback. Effective diagnostic systems should utilize a thorough framework that incorporates diverse design features customized to the specific characteristics of each learner (Bernacki, Greene, & Lobczowski, 2021).

Essentially, this study seeks to close the divide between theoretical progress and practical use in the classroom, equipping educators with useful tools to assess and improve scientific proficiency. This research aims to create a diagnostic system that integrates machine learning (ML) with intelligent tutoring systems (ITS). The system will provide instant feedback and personalized learning paths, promoting ongoing enhancement of skills. This method is in line with the requirement for immediate reporting and feedback systems to guarantee continuous monitoring and prompt educational interventions (Feng & Heffernan, 2005).

This research holds great significance for multiple reasons. Firstly, it contributes to the scholarly conversation on educational technology by presenting empirical evidence on the effectiveness of integrating machine learning (ML) and intelligent tutoring systems (ITS) in identifying and improving scientific proficiency. Furthermore, it provides educators with practical answers, giving them with sophisticated tools to enhance the outcomes of science education. This study seeks to enhance the quality of scientific education in Thailand by focusing on the unique requirements of seventh-grade students. Its objective is to bring the education system in line with worldwide standards and provide students with the necessary skills to tackle future difficulties. Research conducted by Singh et al. (2022) has demonstrated that the combination of Intelligent Tutoring Systems (ITS) and Machine Learning (ML) has a substantial positive impact on student performance and satisfaction when compared to conventional teaching approaches.

The rationale for combining machine learning (ML) and intelligent tutoring systems (ITS) in educational diagnostics is substantiated by current scholarly research and empirical evidence. Jordan and Mitchell (2015) highlight the significance of machine learning in developing precise predictive models that can effectively identify learning inadequacies. In addition, Intelligent Tutoring Systems (ITS) have been shown to be effective in adjusting to individual learning demands and provide prompt feedback, as evidenced by the studies conducted by Stankov et al. (2008) and Conati (2009). The suggested diagnostic system intends to utilize these technologies to fill the existing gaps in scientific education and offer a scalable solution to improve students' learning development. The theory-guided approach guarantees that tailored adjustments are methodically synchronized with learner characteristics and targeted learning results (Bernacki, Greene, & Lobczowski, 2021). Therefore, the research objective was to investigate the effects of a diagnostic system for scientific competency, combined with a personalized intelligent tutoring module that uses machine learning, on the learning progress of seventh-grade students.

LITERATURE REVIEW

System Diagnostic Design

The design of a diagnostic system is crucial for assessing and enhancing students' competencies. It typically involves stages such as pre-assessment, activity planning, and post-assessment, as described by Houston (1972) and Lavrenc (1973). These stages ensure that learning objectives are clear, activities are planned to meet these objectives, and outcomes are evaluated to provide feedback for further learning. Putcharee Junpeng et al. (2020) validated a digital tool for diagnosing mathematical proficiency in Thai seventh-grade students, demonstrating the system's effectiveness in providing accurate, consistent, and stable assessments.

Educational Units

Learning modules and Intelligent Tutoring Systems (ITSs) are designed to support individualized learning experiences. Houston (1972) states that good learning modules comprise a prospectus, objectives, pre-assessment, activities, and post-assessment. Lavrenc (1973) highlighted the significance of doing an initial assessment, implementing specific activities, and conducting a final evaluation in order to gauge the achieved learning outcomes. Intelligent tutoring systems (ITSs) employ artificial intelligence to customize information and tactics according to the specific requirements of each learner, hence improving the learning experience (Gamboa & Fred, 2012; Dağ & Erkan, 2003).

Diagnostic Report Formats

Diagnostic reports play a significant role in communicating assessment results. Mattern & Packman (2009) classified these reports into individual student score reports, roster score reports, and summary test reports. Hambleton & Zenisky (2012) outlined a seven-step process for developing effective reports, which includes defining the purpose, identifying the audience, reviewing relevant literature, designing the report, collecting data, revising the report, and implementing and monitoring the report's use. Junpeng et al. (2020) highlighted the importance of detailed diagnostic feedback in enhancing students' learning experiences.

Machine Learning

Machine learning (ML) is an essential component of contemporary diagnostic systems, providing techniques to acquire knowledge from data and enhance predictive capabilities as time progresses (Langley & Simon, 1995; Mahesh, 2020). Machine learning algorithms can be classified into three main categories: supervised learning, unsupervised learning, and reinforcement learning (Shalev-Shwartz & Ben-David, 2009). Decision trees, which are a sort of machine learning algorithm, are highly beneficial for tasks involving classification and regression. This makes them well-suited for educational diagnostics (Quinlan, 1986).

Intelligent Tutoring Module

Intelligent tutoring module utilize artificial intelligence to create customized learning environments that adapt to the specific demands of each student. The systems have essential modules like the information base, student module, educational module, and interface module (Wenger, 1987; Feng-Jen Yang, 2010). Intelligent Tutoring Systems (ITSs) are an improvement over traditional computer-assisted instruction because they provide individualized assistance and immediate feedback, which improves the whole educational experience (Conati, 2009; Koedinger & Corbett, 2006).

As a whole, these components together contribute to the creation of advanced educational technologies that diagnose and improve student learning through individualized and adaptive methods.

METHODS

This research is part of a broader design research methodology (Vongvanich, 2020) focused on improving educational practices through innovative technological interventions. This design was developed based on the research framework established by Junpeng et al. (in progress), who conducted a research project titled "Designing and Developing Intelligent Personalized Diagnostic and Tutorial System for Enhancing Mathematical Proficiency Progressions of Students through Machine Learning."

The current research extends and builds upon Junpeng's work by adapting and applying their methodologies to the context of scientific competency development among seventh-grade students. The study, as presented in this article, involves two primary steps: (1) the development of a predictive model to diagnose the scientific competency levels of seventh-grade students using machine learning techniques, specifically employing decision tree methodologies as outlined by Quinlan (1986) and enhanced by contemporary work, such as that by Maestrales et al. (2021); and (2) the design and implementation of a diagnostic system integrated with a personalized intelligent tutoring module.

This system is intended to enhance the learning progression of seventh-grade students by using machine learning to deliver tailored educational support. The study investigates the effect of this combined approach on the learning progression of seventh-grade students. The research methodology consists of the following steps:

Development of a Predictive Model for Diagnosing Scientific Competency Levels Using Machine Learning Through Decision Tree Techniques

This step focuses on the efficiency of the predictive model using machine learning combined with an intelligent tutoring module and the interaction between the predictive model and the intelligent tutoring module that affects individual learners' scientific competency levels. The steps are as follows:

Data Sources

Secondary data was collected from the responses of 847 seventh-grade students, covering all ability levels (high, medium, and low) and considering the size of the schools and the results of the scientific competency test (Intasoi et al., 2020).

Procedures

Data Collection: Secondary data collection includes test responses, students' basic information, total scores in each dimension, and scientific competency levels in each dimension.

Analysis: The analysis of scientific competency levels using machine learning through decision tree techniques was conducted using Python programming on Google Colaboratory. The predictive model's performance in each dimension is as follows: Three 3-level decision tree models assessed scientific competency. ES had 0.68 accuracy and 0.59 error. ED had 0.68 accuracy and 0.56 error. IE had 0.62 accuracy and 0.87 error. In summary, the accuracy of the scientific competency dimensions is acceptable, with accuracy values of 0.60 or higher (Mesarić & Šebalj, 2016) as shown in the Table 1.

Table 1 ***Predictive Model Performance***

Level	Precision	Recall	F-measure	Accuracy	Error
Dimension of Explanation of Scientific Phenomena (ES)					
1	0.80	0.72	0.76	0.68	0.59
2	0.59	0.67	0.63		
3	0.57	0.66	0.61		
4	0.86	0.67	0.76		
Evaluation and Design of Scientific Inquiry (ED)					
1	0.78	0.84	0.81	0.68	0.56
2	0.52	0.52	0.52		
3	0.67	0.69	0.68		
4	0.93	0.56	0.70		
Interpretation of Data and Use of Evidence (IE)					
1	0.74	0.87	0.80	0.62	0.87
2	0.32	0.31	0.31		
3	0.30	0.17	0.22		
4	0.72	0.77	0.75		

The decision tree diagrams showing the predictive models for scientific competency levels in each dimension, obtained from Python programming on Google Colaboratory, are illustrated in the following images, as shown in Figure 1-3.

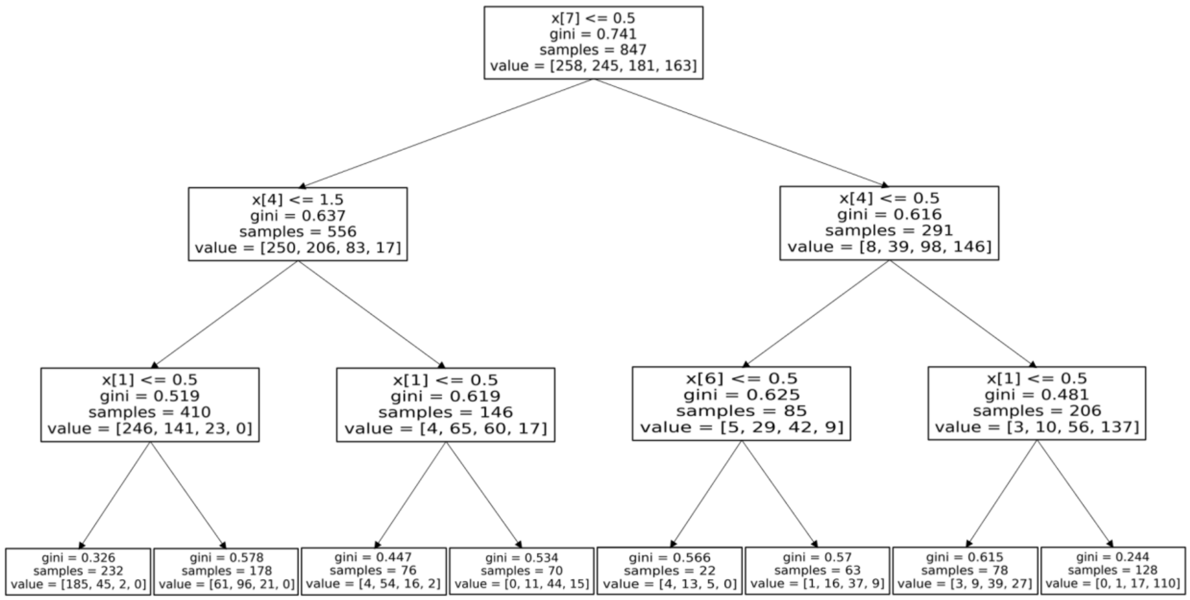

Figure 1 Decision Tree Diagram for Explanation of Scientific Phenomena (ES)

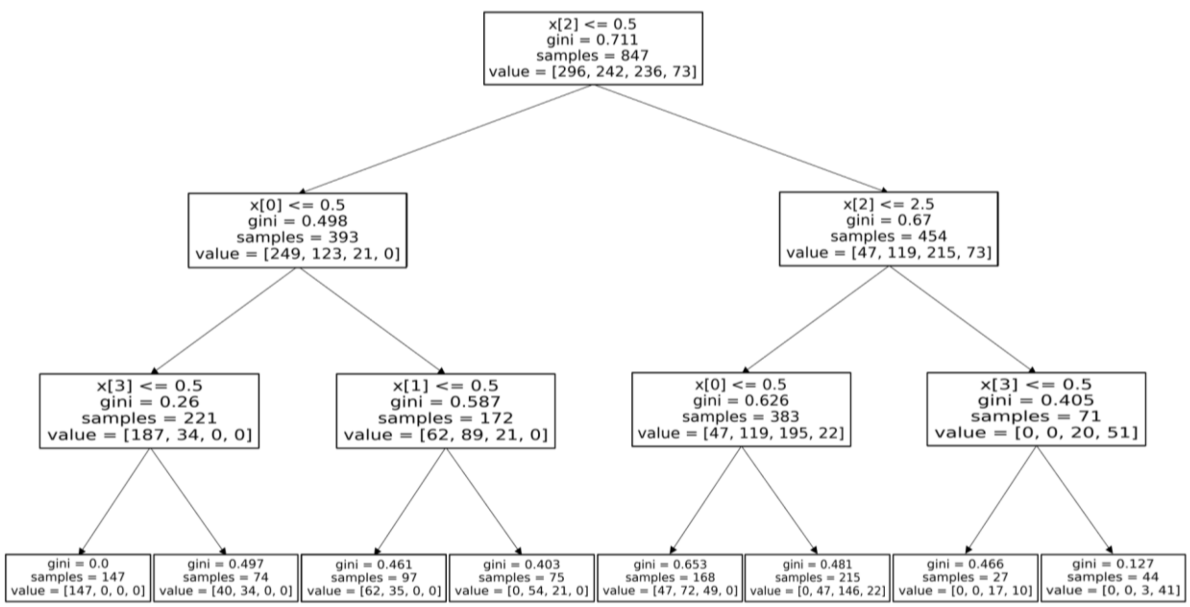

Figure 2 Decision Tree Diagram for Evaluation and Design of Scientific Inquiry (ED)

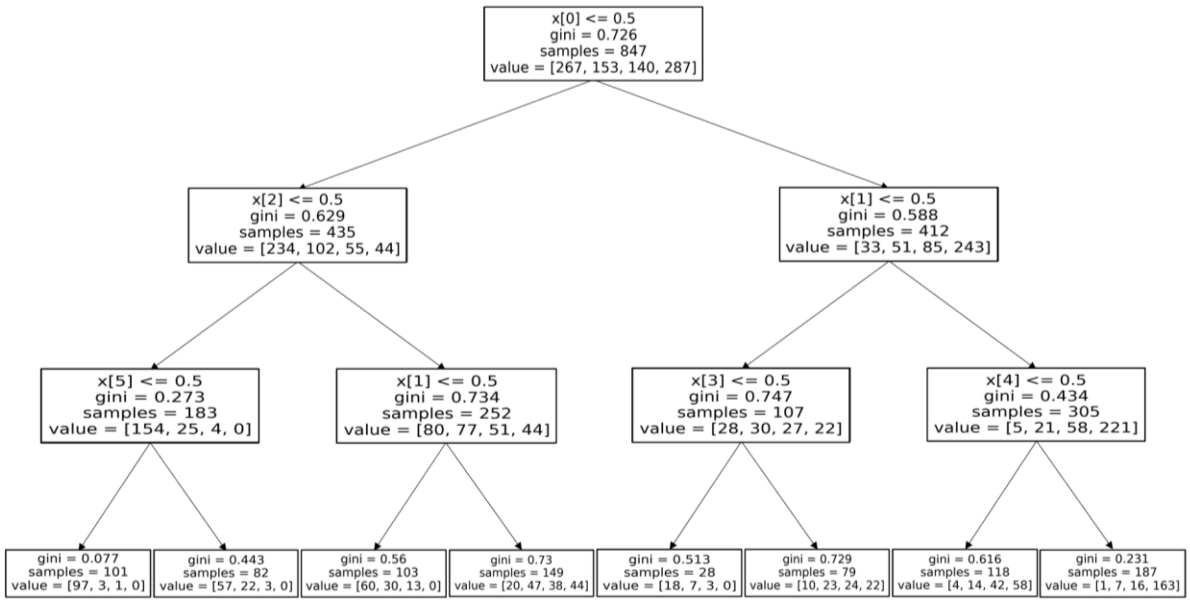

Figure 3 Decision Tree Diagram for Interpretation of Data and Use of Evidence (IE)

Design and Testing of the Diagnostic System Combined with a Personalized Intelligent Tutoring Module Using Machine Learning

Population and Sample

The population includes 5,932 seventh-grade students in Chaiyaphum Secondary Education Service Area. The sample size was determined using G*Power software, resulting in 88 students each for the experimental and control groups. Schools were randomly selected based on their readiness in technology, willingness to cooperate in the research, and varying levels of students' mathematical abilities. Three schools were selected, and two seventh-grade classrooms were randomly chosen from each school, resulting in six classrooms in total. Systematic random sampling was used to assign odd-numbered students (1, 3, 5, ...) to the experimental group and even-numbered students (2, 4, 6, ...) to the control group, ensuring equal representation.

System Evaluators

User satisfaction with the human-computer interface was evaluated by 181 participants, including 176 students from the sample and 5 experts. Heuristic and standard evaluations of the system quality were conducted by 5 experts chosen through purposive sampling.

Tools Used

Multidimensional diagnostic tests of scientific competency for seventh-grade students, covering three dimensions: explanation of scientific phenomena (10 items), evaluation and design of scientific inquiry (4 items), and interpretation of data and use of evidence (8 items) (Intasoi et al., 2020), Standard evaluation tools, Heuristic evaluation checklists and User satisfaction surveys for the human-computer interface.

Procedures

Design: The diagnostic system, combined with a personalized intelligent tutoring module using machine learning, was specifically designed to enhance the learning progress of these students. Learning pathways for diagnosing scientific competency were developed using machine learning analysis. The intelligent tutoring module was designed to provide personalized feedback, with modules categorized into four levels: High Level, Intermediate Level, Basic Level, and Below Basic/Starter Level. Automated scoring and feedback mechanisms were incorporated, providing feedback in four formats: retry, guidance, detailed explanation, and full solution. This research thus expands on Junpeng's foundational work by focusing on the domain of scientific education and further refining the feedback mechanisms to better support student learning in this area.

The overall operation of the system is divided into 4 parts: (1) Student module; (2) Knowledge base module; (3) Pedagogical module or Intelligent tutoring module and (4) Interface module or Personalized reporting can be explained as follows:.

Part 1: Student Module is the part that shows about learning ability. Academic efficiency learning progress learning style Academic history and the test history of the students, consisting of 3 parts: 1) the import data section It is the part where data must be imported into the system. For use in diagnosing the ability level of individual learners. Contains information about the school used for testing, including the school code and school list. Student ID For students to fill out their username and password before proceeding with the exam. 2) Processing section: This is the part where the data received from the imported data section is used in the diagnostic process. Focusing on the program process (algorithm) and 3) the skill level diagnosis section. It is part of reporting the level of scientific competency of individual students in each dimension. Various information for students Teachers and stakeholders

Part 2: Knowledge Base Module is the part that shows how to create problems, tests, or assign tasks that are appropriate for students. Presents the expected behavior of the learners and actual behavior from the assessment of the learner's knowledge. This is a section that explains more at each skill level. It consists of 5 parts: 1) Input data section. It is the part where data must be imported into the system. To be used in diagnosing the student's ability level, consisting of questions and question situations used in diagnosing the student's scientific competency level. All possible correct answer formats 2) Recent proficiency 3) Misconception) 4) Suggestions and 5) Recommendations

Part 3: Pedagogical Module (Intelligent Tutoring Module) is the part that shows about providing feedback. Guidelines for finding answers learning media Explaining the process and reasons To provide assistance to students Including tracking and evaluating student learning while using it, consisting of 2 parts: 1) intelligent supplementary lessons It is the section that provides intelligent supplementary lessons according to the student's ability level in each dimension 2) The section provides feedback. It is part of the system for providing feedback on each item. The system will display the format for providing feedback for each question. Which is presented in the form of 4 types of hints: 1) try again, 2) give guidance on how to find the answer, 3) explain in detail or give an example, and 4) explain in detail and answer. In the event that the student answers incorrectly or does not answer

Part 4: Interface Module (Personalized Reporting) is a section that shows the results of the diagnosis of students' ability levels (diagnosis) and the progress of students in each dimension after receiving individual intelligent tutoring lessons (Tutorial) by presenting the test results. and student assessment results The system will also process the total score that students receive in each dimension of science competency. Report on the scientific competency level of individual learners. and provide additional information about the description of the proficiency level in each dimension, including recent proficiency, misconception, suggestions and recommendations, in which each dimension is divided into 5 levels: below basic level/starter level, basic level, intermediate level, and high level. Here are some design examples:

(a) Design of Learning Pathways in Each Dimension, as shown in the Figure 4.

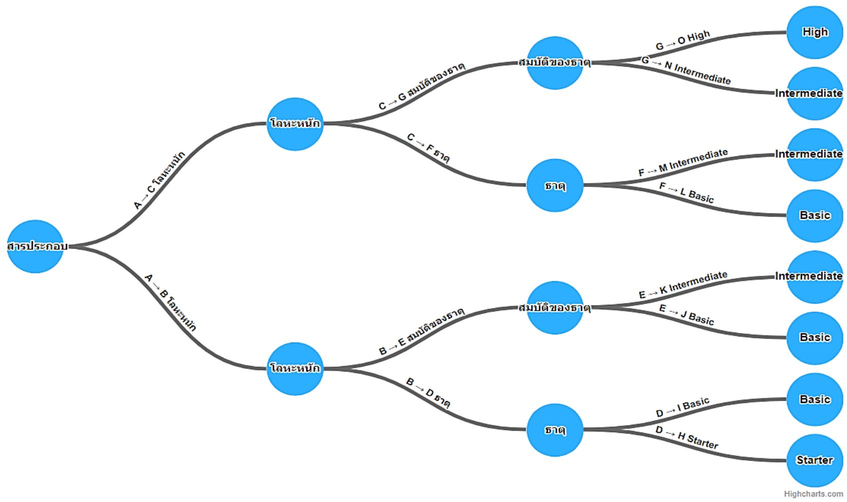

Figure 4 *Example of Learning Pathway Design in Each Dimension*

(b) Login to the system via the website http://exml.itassess.com. Then, students must enter their school name, username, and password. The examination consists of situational and mixed-type questions, divided into two sections: multiple-choice and subjective questions. These two sections are on different pages of the examination, as shown in the Figure 5.

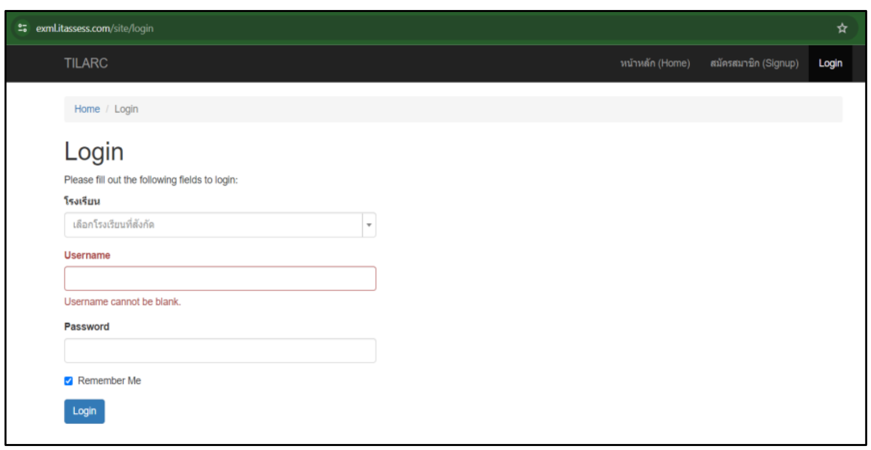

Figure 5 System Login Interface

(c) The processing section involves using the data obtained from the input section for the diagnostic process, focusing on the program's algorithm. The diagnostic section reports individual students' scientific competency levels in each dimension, providing various information for students, teachers, and stakeholders as shown in the Figure 6.

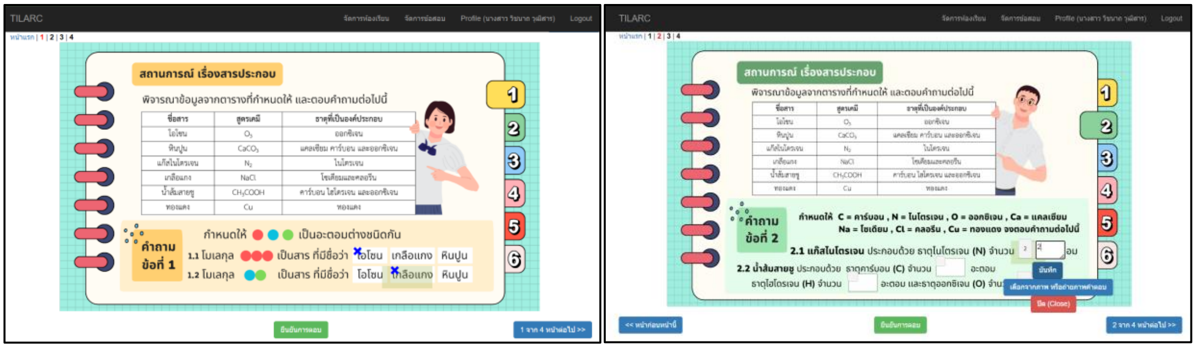

Figure 6 Example Screens of Multiple-Choice and Open-Ended Questions

(5) Reporting results after engaging with the Intelligent Tutoring System (Tutorial). The system will display the assessment results indicating whether each student's scientific competency in each dimension remains at the same level or has progressed to a higher level, as shown in the Figure 7-8.

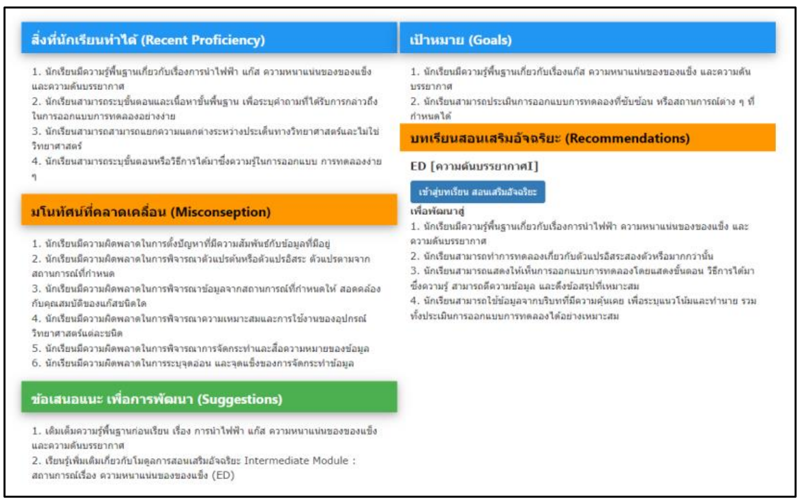

Figure 7 *Example of Individual Scientific Competency Level Report*

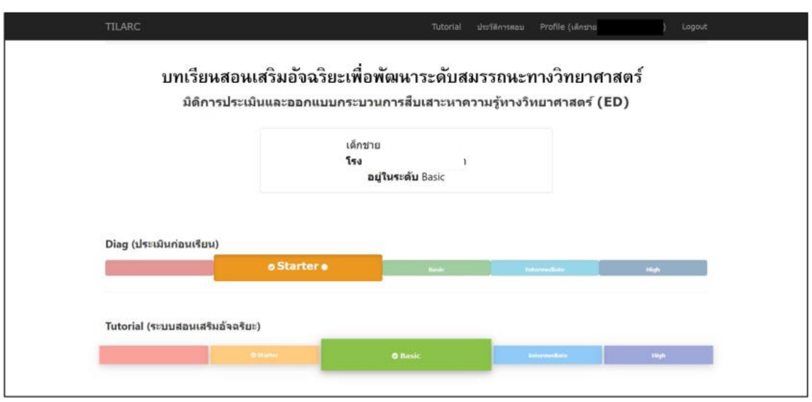

Figure 8 Example of Intelligent Tutoring Module Report

Implementation: The system was tested with the sample groups, refined, and evaluated for consistency between total scores in each dimension, scientific competency levels, and individual learning progress.

Quality Assessment: Experts assessed the system quality using heuristic evaluation. Post-test satisfaction surveys were administered to students and teachers, evaluating screen, terminology, system information, and system capabilities.

Data Analysis

Descriptive Statistics

Descriptive statistics were used to analyze the scientific competency levels of students in each group before and after the intervention. The mean and standard deviation for each dimension (ES, ED, and IE) were calculated for both the control and experimental groups.

Learning Progression

The relative learning progression for each dimension (ES, ED, and IE) was calculated to compare the improvement in scientific competency levels from pre-test to post-test. The mean learning progression and standard deviations were computed for both the control and experimental groups. The learning progression of students can be measured by comparing their scores before and after a learning intervention. The formula used is based on the relative gain score method (Kanjanawasri, 2013). which is calculated as follows:

$$\text{Learning Progression (\%)} = \frac{(Y - X)}{(F - X)} \times 100$$

Where:

X = Pre-test score (score before learning)

Y = Post-test score (score after learning)

F = Maximum possible score

This formula calculates the percentage of learning progression, reflecting how much a student has improved relative to the maximum possible improvement. A higher percentage indicates greater learning progression. The criteria categorize students' learning progression into five levels based on their percentage scores: advanced, high, intermediate, initial, and no progression.

Multivariate Analysis of Variance (MANOVA)

A one-way MANOVA was conducted to compare the scientific competency learning progression across different study groups. The multivariate tests, including Pillai's Trace, Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root, were used to assess the overall effect of the intervention on the dependent variables (scientific competency levels in ES, ED, and IE). The significance levels were set at $p < .05$ to determine statistical significance.

Tests of Between-Subjects Effects

Further analysis involved Tests of Between-Subjects Effects to examine the impact of the group (control vs. experimental) on the learning progression in each dimension. The Type III Sum of Squares, degrees of freedom (df), Mean Square, F value, and significance level (p-value) were calculated to determine the differences between groups.

RESULTS

The effect of a diagnostic system for scientific competency combined with a personalized intelligent tutoring module through machine learning for enhancing the learning progression of seventh-grade students was tested with two groups: the control group, which received the intelligent tutoring module without interactive feedback, and the experimental group, which received both the intelligent tutoring module and interactive feedback. The scientific competency levels in each dimension were categorized into four levels: Below Basic Level/Starter Level (0 points), Basic Level (1 point), Intermediate Level (2 points), and High Level (3 points), and these competency levels were analyzed using descriptive statistics. The results were as follows:

Comparison of Scientific Competency Levels in Each Dimension

Explanation of Scientific Phenomena (ES): The control group had a mean score of 1.43 (S.D. = 0.94), while the experimental group had a mean score of 1.60 (S.D. = 1.07). Evaluation and Design of Scientific Inquiry (ED): The control group had a mean score of 1.20 (S.D. = 0.87), while the experimental group had a mean score of 1.39 (S.D. = 0.94). Interpretation of Data and Use of Evidence (IE): The control group had a mean score of 1.23 (S.D. = 0.94), while the experimental group had a mean score of 1.58 (S.D. = 0.99).

The average scientific competency scores of the experimental group were higher than those of the control group across all three dimensions, as shown in the Table 2.

Table 2 ***Scientific Competency Levels by Dimension***

Scientific Competency Level	Group	Full Score	N	$\bar{X}$	S.D.
ES	Control Group	3	88	1.43	0.94
	Experimental Group	3	88	1.60	1.07
ED	Control Group	3	88	1.20	0.87
	Experimental Group	3	88	1.39	0.94
IE	Control Group	3	88	1.23	0.94
	Experimental Group	3	88	1.58	0.99

Comparison of Learning Progression Scores in Each Dimension

The researcher used scores from the diagnostic system, including interactive feedback and the intelligent tutoring module, to assess the scientific competency levels in each dimension: ES, ED, and IE. The competency levels were compared before (diagnosis) and after (tutorial) receiving the intelligent tutoring module using relative progression scores.

The highest average progression score was in the ES dimension, with a mean of 40.25 (S.D. = 36.49), followed by the IE dimension with a mean of 39.58 (S.D. = 34.16), and the lowest in the ED dimension with a mean of 35.42 (S.D. = 31.35). The experimental group had higher average learning progression than the control group across all three dimensions, as shown in the Table 3.

Table 3 ***Scientific Competency Progression Scores***

Development Scientific Competency Level	Group	N	$\bar{X}$	S.D.	Learning Progression Level
ES	Control Group	88	34.47	33.50	Intermediate
	Experimental Group	88	46.02	38.57	Intermediate
	Total	176	40.25	36.49	Intermediate
ED	Control Group	88	29.92	28.61	Intermediate
	Experimental Group	88	40.91	33.13	Intermediate
	Total	176	35.42	31.35	Intermediate
IE	Control Group	88	33.52	31.51	Intermediate
	Experimental Group	88	45.64	35.78	Intermediate
	Total	176	39.58	34.16	Intermediate

The scientific competency learning progression for the experimental group were higher than those for the control group in all three dimensions, as shown in the Table 4.

Table 4 ***Learning Progression Levels of Scientific Competency by Dimension and Group***

Scientific Competency Dimension	Learning Progression Level	Total (N)	Control Group (N)	Experimental Group (N)
ES	Initial Level	60	32	28
	Intermediate Level	58	39	19
	High Level	26	5	21
	Advanced Level	32	12	20
	Total	176	88	88
ED	Initial Level	57	32	25
	Intermediate Level	67	43	24
	High Level	39	7	32
	Advanced Level	13	6	7
	Total	176	88	88
IE	Initial Level	55	30	25
	Intermediate Level	64	43	21

	High Level	32	5	27
	Advanced Level	25	10	15
	Total	176	88	88

The statistical analysis of the model intercept test with four test statistics showed degrees of freedom (df) = 3. The significance levels for Pillai's Trace, Wilks' Lambda, Hotelling's Trace, and Roy's Largest Root were all p = .099, which is statistically significant at the .05 level. This indicates that the studied groups influenced the learning progression of scientific competency levels, as shown in the Table 5.

Table 5 ***One-way MANOVA for Comparing Scientific Competency Development Across Different Study Groups***

Multivariate Tests							
Source of Variation	Test Statistic	Value	F	Hypothesis df	Error df	p	Partial Eta Squared
Intercept	Pillai's Trace	.611	89.908[b]	3.000	172.000	<.001*	.611
	Wilks' Lambda	.389	89.908[b]	3.000	172.000	<.001*	.611
	Hotelling's Trace	1.568	89.908[b]	3.000	172.000	<.001*	.611
	Roy's Largest Root	1.568	89.908[b]	3.000	172.000	<.001*	.611
Group	Pillai's Trace	.036	2.120[b]	3.000	172.000	.099	.036
	Wilks' Lambda	.964	2.120[b]	3.000	172.000	.099	.036
	Hotelling's Trace	.037	2.120[b]	3.000	172.000	.099	.036
	Roy's Largest Root	.037	2.120[b]	3.000	172.000	.099	.036

* Statistically significant at .05 level

The comparison between the control and experimental groups shows that the scientific competency development in the ES dimension had p = .035, in the ED dimension had p = .020, and in the IE dimension had p = .018. Since these p-values are less than .05, it can be concluded that the control and experimental groups had different scientific competency developments, with the experimental group having higher average learning progression scores in all three dimensions, as shown in the Table 6.

Table 6 ***Tests of Between-Subjects Effects***

Tests of Between-Subjects Effects						
Source	Dependent Variable	Type III Sum of Squares	df	Mean Square	F	p
Corrected Model	Progression ES	5872.790[a]	1	5872.790	4.500	.035*
	Progression ED	5309.343[b]	1	5309.343	5.542	.020*
	Progression IE	6464.646[c]	1	6464.646	5.688	.018*
Intercept	Progression ES	285077.336	1	285077.336	218.416	<.001*
	Progression ED	220763.889	1	220763.889	230.425	<.001*
	Progression IE	275763.889	1	275763.889	242.618	<.001*
Group	Progression ES	5872.790	1	5872.790	4.500	.035*
	Progression ED	5309.343	1	5309.343	5.542	.020*
	Progression IE	6464.646	1	6464.646	5.688	.018*
Error	Progression ES	227105.429	174	1305.204		
	Progression ED	166704.545	174	958.072		
	Progression IE	197771.465	174	1136.618		
Total	Progression ES	518055.556	176			
	Progression ED	392777.778	176			
	Progression IE	480000.000	176			

* Statistically significant at .05 level

The graphs below illustrate the average scientific competency learning progression scores for each dimension, as shown in the Figure 9-11.

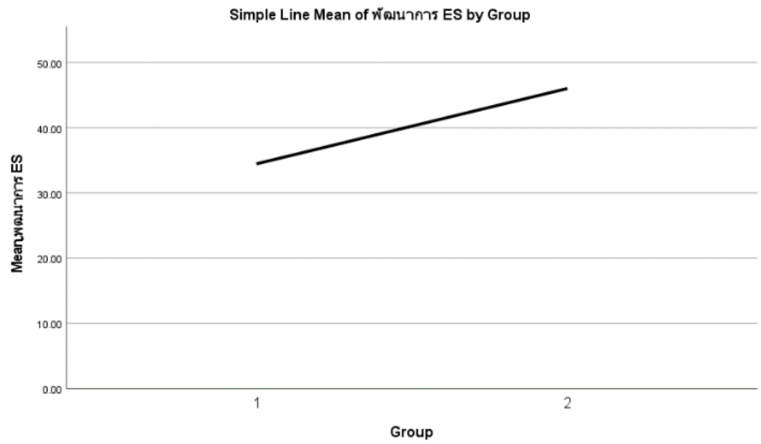

Figure 9 Graph of Average Scientific Competency Learning Progression Scores for the Dimension of Explanation of Scientific Phenomena (ES)

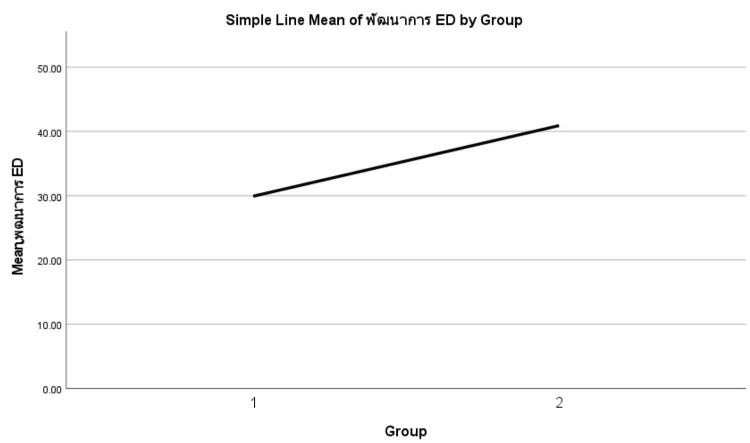

Figure 10 Graph of Average Scientific Competency Learning Progression Scores for the Dimension of Evaluation and Design of Scientific Inquiry (ED)

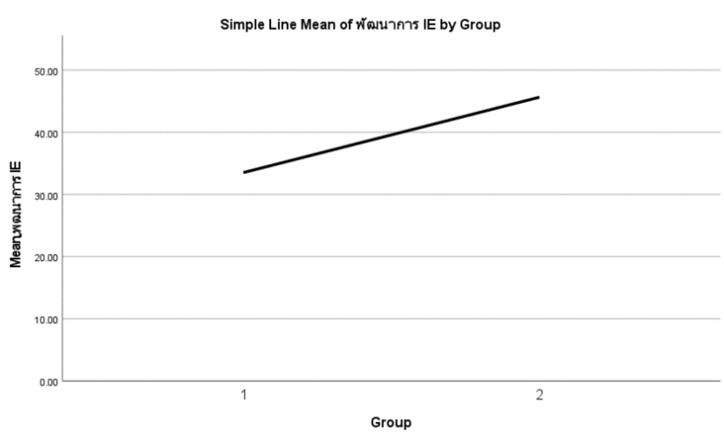

Figure 11 Graph of Average Scientific Competency Learning Progression Scores for the Dimension of Interpretation of Data and Use of Evidence (IE)

These results demonstrate that the experimental group achieved higher scientific competency learning progression scores compared to the control group across all three dimensions.

Quality of the Diagnostic System Combined with a Personalized Intelligent Tutoring Module Through Machine Learning

The quality of the diagnostic system combined with a personalized intelligent tutoring module was assessed by experts in scientific content and teaching, measurement and evaluation, and technology. The quality evaluation results are as follows:

Evaluation Standard Results

The system was evaluated against five criteria: Utility Standards, Feasibility Standards, Propriety Standards, Accuracy Standards, and Evaluation Accountability Standards. The individual mean scores were high for Utility (4.43), Feasibility (4.30), and Accountability (4.47) standards, and very high for Propriety (4.71) and Accuracy (4.50) standards. The overall evaluation score was very high, with a mean score of 4.50 and a standard deviation of 0.55.

Heuristic Evaluation Results

Thirteen items were evaluated, and the overall evaluation score was high, with a mean score of 4.40 and a standard deviation of 0.62. Specific items scored very high, including Match between system and the real world (4.60), Consistency and standards (4.60), Flexibility and efficiency of use (4.60), Aesthetic and minimalist design (4.80), Support and extend the user's current skills (4.60), and Protect the personal information (4.60). Other items, such as Visibility of system status (4.20), User control and freedom (4.00), and Error prevention (3.80), scored high.

User Satisfaction Evaluation

User satisfaction with the human-computer interface was evaluated across three aspects: Screen, Terminology and system information, and System capabilities. The overall evaluation score was high, with a mean score of 6.89 and a standard deviation of 1.96, as shown in the Table 7.

Table 7 ***User Satisfaction Evaluation of the Diagnostic System for Scientific Competency***

No.	Evaluation Item	$\bar{X}$	S.D.	Consideration Level
1	Screen	6.95	1.93	High
2	Terminology and system information	6.93	1.96	High
3	System capabilities	6.76	1.99	High
Overall		6.89	1.96	High

In conclusion, the design and implementation of the diagnostic system combined with a personalized intelligent tutoring module through machine learning significantly enhanced the learning progress of seventh-grade students. The system was found to be reliable, of high quality, and well-received by the students.

DISCUSSIONS AND RECOMMENDATIONS

Evaluation of Coherence

The evaluation of the consistency of situations, content scope, questions, and scoring in diagnosing the three dimensions of scientific competency revealed that all three dimensions Explanation of Scientific Phenomena (ES), Interpretation of Data and Use of Evidence (IE), and Evaluation and Design of Scientific Inquiry (ED) demonstrated a high level of coherence. This validates the initial hypothesis that implementing an intelligent coaching module with automated feedback can enhance students' scientific competency. This finding aligns with the research conducted by Thongproh (2022), which highlighted the importance of automated scoring and feedback in rectifying conceptual misunderstandings to improve scientific expertise. Moreover, the integration of adaptive assessment in AI-driven education ensures a standardized evaluation by constantly adjusting the content and difficulty level based on students' responses, thereby providing a precise assessment of their ability (Iqbal, 2023). In addition, the integration of carefully designed architectural features in Intelligent Tutoring Systems (ITS) ensures a structured evaluation and personalized feedback, resulting in improved educational outcomes (Alkhatlan & Kalita, 2018).

The adaptive feature of "Seis Tutor" improves its consistency by tailoring feedback and learning paths to cater to the unique requirements of individual students, thereby offering a precise evaluation of their ability (Singh et al., 2022). AI-powered Intelligent Tutoring Systems (ITS) maintain evaluation consistency by adapting to each student's responses and providing personalized feedback (Van Vaerenbergh & Pérez-Suay, 2021). Intelligent Tutoring Systems (Anohina, 2007) utilize adaptive help mechanisms, namely a two-layer model of suggestions and problem-solving modes, to ensure a dependable evaluation and feedback system. AI methodologies, such as symbolic AI and machine learning, provide a trustworthy and consistent structure for evaluating student performance, hence enhancing the reliability of educational assessments (Richard et al., 2023).

Assistment and other real-time reporting technologies enhance the dependability of evaluating student achievement by providing immediate and continuous feedback. This guarantees that educational interventions are administered promptly and with a specified focus (Feng & Heffernan, 2005). Regular monitoring of student attributes enables the flexible evaluation and methodical tailoring of instruction, hence guaranteeing consistent and effective educational results (Tetzlaff, Schmiedek, & Brod, 2020). Utilizing a theory-guided approach in developing PL (Personalized Learning) settings ensures consistency by aligning personalized adaptations with established educational theories. This technique methodically considers learner characteristics and desired outcomes (Bernacki, Greene, & Lobczowski, 2021). Machine learning can also evaluate beyond performance. Machine learning models enhance the consistency of evaluating emotional and psychological states by analyzing facial expressions, which ensures reliable diagnostic outcomes (Kryshtanovych et al., 2024).

Analysis of Learning Progression Scores

Upon analyzing the progression scores in each dimension of scientific competency, it was found that the ES dimension had the highest scores, followed by the IE dimension, whilst the ED dimension had the lowest values. This indicates that students still lack the skills to evaluate and develop scientific research methodologies. These limitations may stem from a lack of knowledge about scientific equipment and a limited understanding of crucial experimental procedures. Furthermore, the development of expertise in ED requires active participation in well-executed interactions that involve the use of scientific apparatus (Taale & Antwi, 2012). The "Seis-Tutor" strategy focuses on addressing specific weaknesses by tailoring the curriculum to match the learner's profile. This method aims to improve areas where students show limited improvement (Singh et al., 2020). AI systems possess the capability to observe and evaluate the academic progress of students, enabling tailored interventions to boost the growth of certain skills, hence enhancing total proficiency (Van Vaerenbergh & Pérez-Suay, 2021).

Comparative Analysis

After analyzing the scientific competency scores in each dimension, it was discovered that the average scores of the experimental group were higher than those of the control group in all aspects. This finding indicates that the use of intelligent coaching modules and timely feedback helps students identify and correct their areas of weakness. This aligns with the concepts proposed by Duppenthaler (2002) and Clifford (1981), who emphasized the importance of delivering prompt feedback and positive reinforcement to enhance motivation for learning.

The dynamic properties of systems like "Seis-Tutor" are enhanced by their capacity to continuously adapt the curriculum based on real-time feedback from learners, hence enhancing academic performance (Singh et al., 2020). Furthermore, adaptive exams enhance engagement by presenting questions that stimulate students without being overly difficult, hence maintaining motivation and focus (Iqbal, 2023). Meta-analyses demonstrate that Intelligent Tutoring Systems (ITS) have a significant beneficial effect on student performance. Research undertaken by Alkhatlan and Kalita (2018) and VanLehn (2011) has shown that step-based tutoring is nearly as effective as human tutoring. Studies indicate that adaptive and personalized systems, like "Seis Tutor," significantly enhance student performance and satisfaction in comparison to traditional systems (Singh et al., 2022).

The implementation of scaffolding questions and rapid feedback in the Assistment system improves student performance, demonstrating the advantages of individualized and flexible learning environments (Razzaq et al., 2007). Intelligent tutoring systems (ITS) that utilize artificial intelligence (AI) improve student performance by offering personalized learning paths and immediate feedback, hence enhancing learning outcomes (Van Vaerenbergh & Pérez-Suay, 2021). Intelligent Tutoring Systems (ITS) employ adaptive problem-solving methods and hint models to enhance student performance by offering prompt and personalized feedback (Anohina, 2007). AI-driven digital environments enhance student performance through real-time feedback and personalized learning experiences, leading to higher average scores in experimental groups (Richard et al., 2023).

Real-time reporting systems that provide comprehensive data boost student performance by enabling educators to make instructional choices based on that data. This, in turn, leads to higher average scores in experimental groups who use intelligent tutoring systems (Feng & Heffernan, 2005). According to Tetzlaff, Schmiedek, and Brod (2020), intelligent tutoring systems that adjust to the specific demands of each student result in superior learning outcomes when compared to traditional educational methods.

Assessment of the Quality of Diagnostic System Design

The diagnostic system, when combined with a customized intelligent training module, underwent a quality assessment utilizing machine learning. Both the normal assessments and heuristic evaluations consistently showed that the system achieved the top ratings. The level of user satisfaction was exceptionally high, particularly with regards to the screen design. The researcher suggests that a visually appealing and user-friendly design can increase students' motivation to learn, which is consistent with the findings of Sirisuthi and Chantarasombat (2021) study that reported a high degree of satisfaction with the module. The user interface of the "Seis-Tutor" system, designed to be user-friendly and visually appealing, has a significant impact on user satisfaction and learning outcomes (Singh et al., 2020). Moreover, adaptive assessment systems conform to the principles of individualized learning by tailoring the evaluation technique for each student. This ensures that the specific needs of every student are effectively addressed (Iqbal, 2023). An intuitive and adaptable interface is essential in an Intelligent Tutoring System (ITS) to guarantee high user satisfaction and facilitate outstanding learning outcomes (Alkhatlan & Kalita, 2018).

An optimal diagnostic system in programming languages (PL) should encompass a comprehensive framework that seamlessly incorporates diverse design components tailored to the distinct attributes of each student. This guarantees that the system effectively accommodates the unique requirements of learners (Bernacki, Greene, & Lobczowski, 2021). The research highlights the importance of effective feedback and the use of technology in teaching to enhance learning. However, there are limitations regarding the use of electronic devices in education, which may not be widespread among all students. Future development of comprehensive feedback systems that consider students' emotional and cognitive factors to improve learning experiences is crucial.

CONCLUSION

Using intelligent tutoring modules and providing immediate feedback significantly enhances students' scientific competency. This research supports the idea of effective feedback and using technology in teaching to promote learning. The researcher recommends further development and improvement of electronic devices in education to increase learning efficiency. Additionally, practical skills training and increased focus on evaluating and designing scientific inquiry processes are necessary to improve scores in this dimension. Further research should focus on developing comprehensive feedback systems that address all dimensions and consider students' emotional and cognitive factors to enhance the learning experience.

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