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AN ARTIFICIAL INTELLIGENCE-BASED FRAMEWORK FOR DEVELOPING STUDENTS' DIGITAL COMPETENCE IN NETWORK TECHNOLOGIES EDUCATION

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Abstract
This study proposes an artificial intelligence-based framework for developing students' digital competence in Network Technologies education. The framework integrates diagnostic assessment, adaptive learning, virtual laboratories, intelligent feedback, learning analytics, and competency-based evaluation. Students' digital competence was assessed through theoretical knowledge, network configuration skills, cybersecurity awareness, problem-solving ability, independent learning, and responsible use of artificial intelligence tools. A quasi-experimental design was applied to compare traditional instruction with an AI-supported learning environment. The results indicated that the experimental group demonstrated higher achievement, fewer configuration errors, greater independence, and stronger problem-solving performance. The proposed framework supports personalized learning and enables instructors to monitor students' progress through continuous data analysis.

Keywords: Artificial intelligence, digital competence, network technologies, adaptive learning, virtual laboratory, learning analytics, intelligent feedback.

Introduction

Digital transformation has increased the need for specialists who can effectively use, configure, secure, and evaluate network technologies. Therefore, Network Technologies education should develop not only theoretical knowledge but also practical, analytical, and problem-solving skills. Traditional instruction often provides the same materials and tasks to all students despite differences in prior

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knowledge, learning speed, and practical experience. This limits personalization and makes it difficult for instructors to provide timely feedback to every learner. Artificial intelligence can improve this process by analysing students' test results, laboratory activities, errors, task-completion time, and requests for assistance. Based on these data, an AI-supported system can recommend suitable learning materials, adjust task difficulty, identify learning gaps, and provide immediate feedback. In this study, digital competence is considered a combination of theoretical knowledge, practical network configuration, cybersecurity awareness, problem-solving, independent learning, and responsible use of AI tools. The study aims to develop and evaluate an AI-based framework that supports these components in Network Technologies education.

Methods

Research Design. A quasi-experimental design was used. A total of 120 undergraduate students were divided into two groups: a control group of 60 students; an experimental group of 60 students. [1]

The control group studied through standard lectures, electronic materials, and common laboratory tasks. The experimental group used an AI-supported learning environment containing adaptive tasks, virtual laboratories, intelligent feedback, and learning analytics. The study was conducted in three stages:

1. initial diagnostic assessment;
2. implementation of the AI-based framework;
3. final assessment and statistical comparison.

Structure of the AI-Based Framework. The framework consisted of six interconnected components:

1. diagnostic component;
2. content component;
3. adaptive learning component;
4. practical activity component;
5. monitoring and feedback component;
6. assessment component.

The diagnostic component identified students' initial knowledge and practical readiness. The content component provided structured learning modules. The adaptive component selected tasks according to each student's performance. The

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practical component included virtual network laboratories. The monitoring component analysed learning activities, while the assessment component measured competency development. [2]

Table 1. Components of the AI-Based Framework

No.	Component	Main Function	Expected Outcome
1	Diagnostic	Identifies prior knowledge and skills	Initial learner profile
2	Content	Provides structured learning resources	Systematic knowledge acquisition
3	Adaptive learning	Adjusts task difficulty and learning path	Personalized learning
4	Practical activity	Organizes virtual network laboratories	Practical configuration skills
5	Monitoring and feedback	Analyses errors, time, and activity	Timely instructional support
6	Assessment	Measures competence development	Objective learning evaluation

Digital Competence Criteria. Students' digital competence was evaluated through six criteria: theoretical knowledge; network configuration; problem-solving; cybersecurity; independent learning; responsible use of artificial intelligence. [3]
The overall Digital Competence Index was calculated as follows:

$$\mathrm{DCI_i} = 0.20\mathrm{K_i} + 0.25\mathrm{C_i} + 0.20\mathrm{P_i} + 0.15\mathrm{S_i} + 0.10\mathrm{I_i} + 0.10\mathrm{A_i},$$

where:

- ($\mathrm{DCI_i}$) is the digital competence index of student (i);
- ($\mathrm{K_i}$) is theoretical knowledge;
- ($\mathrm{C_i}$) is network configuration;
- ($\mathrm{P_i}$) is problem-solving;
- ($\mathrm{S_i}$) is cybersecurity;
- ($\mathrm{I_i}$) is independent learning;
- ($\mathrm{A_i}$) is responsible use of AI.

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Table 2. Digital Competence Assessment Criteria

No.	Criterion	Indicators	Weight
1	Theoretical knowledge	Network models, protocols, standards, and terminology	20%
2	Network configuration	Router, switch, server, and wireless network setup	25%
3	Problem-solving	Identification and correction of network failures	20%
4	Cybersecurity	Secure configuration and access management	15%
5	Independent learning	Task completion with limited support	10%
6	Responsible AI use	Verification and appropriate use of AI recommendations	10%
	Total		**100%**

The competency levels were interpreted as follows:

- 0–55: basic;
- 56–70: developing;
- 71–85: proficient;
- 86–100: advanced.

Adaptive Learning Mechanism. The AI system analysed the following data: test scores; laboratory performance; number and type of errors; task-completion time; number of attempts; use of instructional support; learning activity. If a student achieved less than 60%, the system recommended additional explanations and simplified tasks. Scores between 60% and 79% resulted in reinforcement activities. Students who achieved 80% or more received more complex laboratory or project tasks. The learner's current performance was estimated using the following formula:

$$\mathrm{LP_i} = 0.30\mathrm{T_i} + 0.40\mathrm{L_i} + 0.20\mathrm{I_i} + 0.10\mathrm{F_i},$$

where:

- ($\mathrm{T_i}$) is the theoretical test score;
- ($\mathrm{L_i}$) is the laboratory result;
- ($\mathrm{I_i}$) is independence;
- ($\mathrm{F_i}$) is learning activity.

Virtual Laboratory and Intelligent Feedback. The virtual laboratory included the following tasks:

- network topology design;
- IPv4 and IPv6 addressing;
- subnetting;

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- VLAN configuration;
- static and dynamic routing;
- DHCP and DNS configuration;
- wireless network security;
- access control lists;
- network monitoring;
- troubleshooting.

The AI assistant analysed students' configuration steps and classified errors. Feedback was provided in three levels:

1. notification that an error existed;
2. indication of the relevant device or configuration section;
3. a detailed hint when the student could not solve the problem independently.

The system avoided giving the full answer immediately. This encouraged students to analyse and correct their own mistakes.

Data Analysis. The mean score was calculated using:

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i \,.$$

The relative improvement was calculated as:

$$RI = \frac{\text{Posttest} - \text{Pretest}}{\text{Pretest}} \times 100$$

An independent-samples Student's (t)-test was used to determine whether the difference between the groups was statistically significant. The significance level was set at ($p<0.05$).

Results

The initial assessment showed that the two groups had similar levels of digital competence. The mean pretest score was 58.3 in the control group and 58.7 in the experimental group. After the intervention, the control group reached an average score of 70.6, while the experimental group reached 83.4. The relative improvement was 21.1% in the control group and 42.1% in the experimental group. [4]

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Table 3. Comparison of Experimental Results

No.	Indicator	Control Group	Experimental Group
1	Pretest mean score	58.3	58.7
2	Posttest mean score	70.6	83.4
3	Absolute improvement	12.3	24.7
4	Relative improvement	21.1%	42.1%
5	Average task-completion time	44.7 min	35.3 min
6	Average errors per laboratory task	4.2	2.1
7	Independently completed tasks	62.5%	85.8%
8	Students at the advanced level	10.0%	33.3%

The greatest differences were observed in network configuration, problem-solving, and independent learning. The experimental group achieved an average network configuration score of 86.1, compared with 69.0 in the control group. The experimental group also made fewer errors in IP addressing, routing, and security configuration. The average number of errors per laboratory task decreased from 4.2 in the control group to 2.1 in the experimental group. Students in the experimental group completed tasks more quickly and requested less direct assistance from the instructor. The percentage of independently completed tasks reached 85.8%, compared with 62.5% in the control group. The statistical analysis indicated that the difference between the final scores of the two groups was significant at ($p<0.001$). This suggests that the improvement was associated with the use of the AI-based framework rather than random variation. [5]

Discussion

The findings show that the AI-based framework improved students' digital competence in Network Technologies education. Its main advantage was the integration of assessment, adaptation, practice, and monitoring within one learning environment. Personalized task selection helped students work at an appropriate level of difficulty. Learners with limited prior knowledge received additional support, while more advanced students completed complex network design and troubleshooting activities. The virtual laboratory strengthened the connection between theory and practice. Students could repeat configurations, test alternative solutions, and observe the consequences of errors without damaging physical equipment. Immediate feedback reduced repeated mistakes

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and supported independent problem-solving. The reduction in task-completion time and error frequency indicates that students developed more systematic configuration strategies. [6]

Learning analytics also improved instructional monitoring. Instructors could identify difficult topics, low-performing students, and common error patterns. This enabled more targeted pedagogical support. However, AI-generated feedback should not be treated as an unquestionable source. Some valid network solutions may differ from predefined configurations. Therefore, the instructor should retain control over complex, creative, and non-standard tasks. The framework also requires responsible data management. Students' activity records, scores, and error histories must be stored securely and used only for educational purposes. [7]

Conclusion

The proposed AI-based framework provides a structured approach to developing students' digital competence in Network Technologies education. It combines diagnostic assessment, personalized learning, virtual laboratories, intelligent feedback, continuous monitoring, and competency-based evaluation. [8] The experimental group demonstrated stronger achievement, fewer errors, faster task completion, and greater independence than the control group. The most significant improvement was observed in network configuration and problem-solving skills. The framework supports instructors by automating routine monitoring and identifying students who need additional assistance. At the same time, human supervision remains essential for evaluating complex solutions and ensuring the fairness of AI-supported decisions. Overall, the framework can be used to improve the practical orientation, personalization, and effectiveness of Network Technologies education.

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