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METHODOLOGICAL JOURNAL**<http://mentaljournal-jspu.uz/index.php/mesmj/index>**EFFECTIVENESS OF AI-BASED ADAPTIVE EDUCATIONAL TECHNOLOGIES IN
DEVELOPING PROFESSIONAL COMPETENCIES OF ENERGY ENGINEERING
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ABOUT ARTICLE

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Abstract: The article evaluates the effectiveness of an artificial intelligence-based adaptive educational technology in the training of energy engineering students. The study aimed to identify changes in professional competency levels and determine whether the experimental and control groups differed statistically. The quasi-experimental study involved 370 students from the Kashkadarya, Jizzakh, Fergana, and Bukhara regions: 187 students in the experimental group and 183 in the control group. The technology combined initial diagnostics, adaptive delivery of theoretical and practical tasks, simulation of professional situations, individualized feedback, and learning-data analysis. Competencies were assessed on a three-level scale; distributions were compared using Pearson's chi-square test, while composite scores were compared using Welch's t-test. Before the intervention, the groups did not differ statistically ($\chi^2 = 0.347$; $p = 0.841$). At the final stage, 56.7% of the experimental group and 36.1% of the control group reached the high level, while the low level was recorded for 13.9% and 31.1%,

respectively. The final distributions differed significantly ($\chi^2 = 21.057$; $p < 0.001$; $V = 0.239$). The normalized composite score reached 80.9% in the experimental group versus 68.3% in the control group ($t = 4.700$; $p < 0.001$; $d = 0.489$). These findings indicate the practical effectiveness of the technology while confirming the instructor's leading role and the need for further studies with stronger control of confounding factors.

Introduction. The digital transformation of higher education is accompanied by a shift from uniform content delivery to systems that account for each learner's actions, pace of progress, and diagnosed knowledge gaps. In this context, artificial intelligence (AI) is used for diagnostics, recommendations, individualized task sequencing, and feedback. However, AI should not be treated as an autonomous substitute for an instructor: educational outcomes depend on sound pedagogical design, transparent criteria, and professional verification of system recommendations [1; 4; 5; 15].

Research reviews show that the principal applications of AI in higher education include intelligent tutoring systems, prediction of learning outcomes, automated assessment, and personalization [2; 3; 15]. Nevertheless, a substantial share of the literature concentrates on the technical accuracy of models, whereas pedagogical effects and the instructor's role are described less consistently [3]. This gap is particularly important in professional education because adaptation must be linked not only to test performance, but also to mastery of methods for solving authentic professional problems.

In the education of energy engineering students, professional competence is demonstrated through the ability to apply theoretical knowledge to electrical-network calculations, analyze equipment operating modes, select and justify engineering solutions, detect errors, and assess energy efficiency. Therefore, individualized learning is appropriate when it guides the student from diagnosis of a specific difficulty to a targeted task, feedback, and repeated verification of the result. This approach is consistent with the principles of personalized adaptive learning and competency-based professional education [6; 11; 14].

Learning analytics constitutes an important resource for adaptation. Data on action sequences, attempts, recurring errors, and performance dynamics help the instructor observe learning between formal assessment points and adjust tasks in a timely manner [7-9]. At the same time, reliable pedagogical decisions require combining digital data with expert

assessment, self-assessment, project work, and portfolios. Reliance on a single automated indicator risks reducing complex professional competence to formally measurable activity.

Accordingly, an empirical evaluation is needed for an adaptive technology in which AI tools are embedded in a pedagogically designed cycle of diagnosis, individualized task assignment, professional action, feedback, and reassessment. The research problem was to establish whether using such a technology is associated with statistically and practically significant changes in the professional competency levels of energy engineering students.

The aim of the study was to evaluate the effectiveness of an AI-based adaptive educational technology by examining changes in students' professional competency levels and differences between experimental and control groups.

The study pursued the following objectives: to describe the pedagogical logic of the technology; compare the groups' initial characteristics; determine the distribution of competency levels after experimental instruction; calculate the statistical significance and effect size of the differences; and identify limitations affecting interpretation of the results.

Materials and methods. Research design and participants

The study used a quasi-experimental comparative design with pre-test and post-test assessment. It involved 370 students enrolled in an educational program related to electric power supply in four regions: 187 students were assigned to the experimental group and 183 to the control group. The distribution of participants is presented in Table 1.

Table 1

Distribution of study participants by region

Region	Experimental group, students	Control group, students	Total, students
Kashkadarya Region	69	64	133
Jizzakh Region	51	50	101
Fergana Region	42	44	86
Bukhara Region	25	25	50
Total	187	183	370

Because the source data did not record individual random assignment, the findings are interpreted as quasi-experimental evidence. The control group studied under the conventional instructional regime, whereas the experimental group used the AI-based adaptive technology. Group comparability before the intervention was tested statistically using the initial distribution of competency levels.

Content of the adaptive technology

The educational technology comprised five interconnected components.

1. Diagnostic component. Entry tasks identified the level of theoretical knowledge, recurring errors, and deficits in practical skills.
2. Adaptive component. Based on the diagnostic profile, each student received tasks of varying complexity and supplementary materials for topics in which difficulties had been detected.
3. Professional simulation component. Students completed tasks approximating future professional activity. In particular, they modeled load distribution at a 110/35 kV electrical substation, determined the power balance, and evaluated transformer efficiency.
4. Feedback component. The system identified inconsistencies in calculations and proposed solutions, while the instructor verified substantive accuracy, explained the causes of errors, and determined the next step in the learning pathway.
5. Assessment and analytics component. The final assessment combined diagnostic and practical tasks, project work, a portfolio, instructor expert assessment, self-assessment, and learning-analytics data.

Preserving the instructor's pedagogical responsibility was a fundamental condition. AI served as a tool for analysis and adaptation rather than an autonomous assessor. This arrangement corresponds to a human-centered approach in which decisions affecting a learner's educational pathway must be understandable, verifiable, and proportionate to the learning objective [4; 10; 12; 13].

Assessment criteria and procedure

Professional competency development was classified at three levels: high, medium, and low. For calculation of the composite indicator, the levels were assigned scores of 3, 2, and 1, respectively. The high level represented independent and well-reasoned solution of professional problems with transfer of knowledge to a modified situation; the medium level represented generally correct performance with occasional difficulties or a need for limited assistance; and the low level represented fragmented knowledge and unstable problem-solving strategies.

The relative frequency of each level within a group was calculated as follows:

$$p_i = n_i / n,$$

where n_i is the number of students at level i and n is the size of the corresponding group.

The mean score was calculated as a weighted sum:

$$\bar{x} = (\sum_{i=1}^3 x_i n_i) / n,$$

where x_i is the score assigned to a level, $x_i \in \{3, 2, 1\}$. For ease of substantive interpretation, the mean score was normalized to the maximum possible value:

$$I = x / 3 \cdot 100\%.$$

Statistical analysis

The distributions across the three competency levels were compared using Pearson's chi-square test for a 2 x 3 contingency table. The strength of association was estimated with Cramer's V. Composite scores were additionally compared using a two-sided Welch's t-test, which does not assume equal variances; 95% confidence intervals and Cohen's d standardized effect size were reported. The significance level was set at 0.05.

Because the original scale is ordinal and the analysis was based on aggregated frequencies, the chi-square test was treated as the primary analytical method. Comparison of mean scores was used as an additional way to represent the direction and practical magnitude of the differences. Calculations were performed using the observed frequencies before rounding the percentages.

Result and discussion. Group comparability at the initial stage

Before implementation of the technology, the distributions of competency levels in the experimental and control groups were similar (Table 2). The high level was demonstrated by 32.1% and 30.6% of students, respectively; the medium level by 36.4% and 35.0%; and the low level by 31.6% and 34.4%. The chi-square test found no significant difference: $\chi^2(2) = 0.347$; $p = 0.841$; Cramer's V = 0.031.

The experimental group had a mean score of 2.005 (SD = 0.800; 95% CI [1.891, 2.120]), while the control group had a mean of 1.962 (SD = 0.808; 95% CI [1.845, 2.079]). The normalized indicators were 66.85% and 65.39%; the difference of 1.45 percentage points was not statistically significant: $t(367.64) = 0.522$; $p = 0.602$; $d = 0.054$. Thus, the baseline data provide no basis for considering either group better prepared.

Table 2

Indicator	Initial: experimental	Initial: control	Final: experimental	Final: control
High level, n (%)	60 (32.1)	56 (30.6)	106 (56.7)	66 (36.1)
Medium level, n (%)	68 (36.4)	64 (35.0)	55 (29.4)	60 (32.8)
Low level, n (%)	59 (31.6)	63 (34.4)	26 (13.9)	57 (31.1)
Mean score	2.005	1.962	2.428	2.049
Normalized indicator, %	66.85	65.39	80.93	68.31

Results at the final stage. After the experimental instruction, the distribution changed substantially (see Table 2 and Figure 1). In the experimental group, the number of students at the high level increased from 60 to 106, or from 32.1% to 56.7%. The number at the low level decreased from 59 to 26, or from 31.6% to 13.9%. In the control group, the share at the high level increased from 30.6% to 36.1%, while the share at the low level decreased from 34.4% to 31.1%.

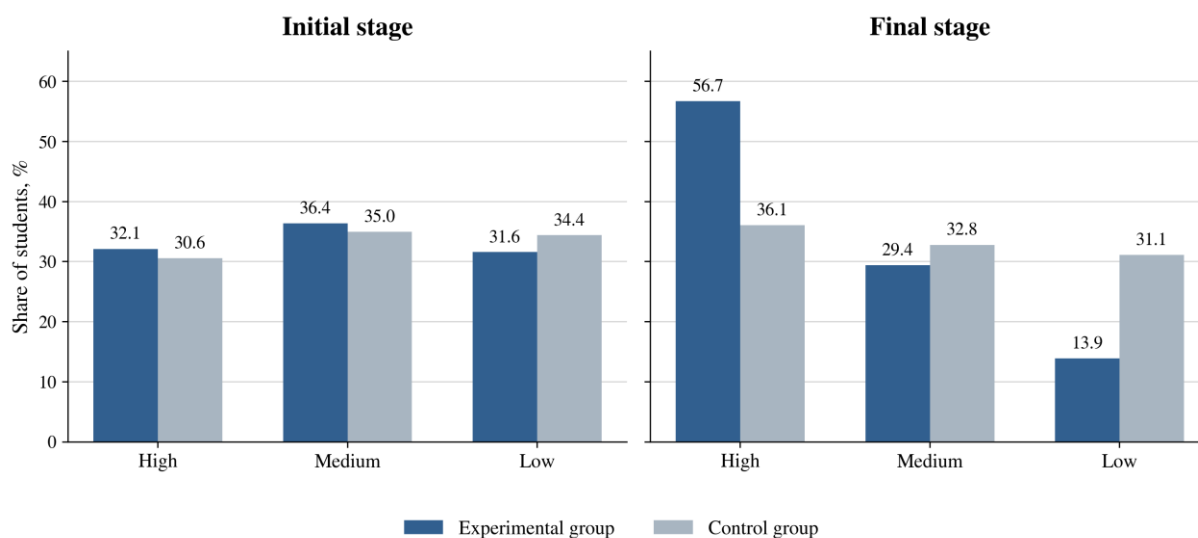


Figure 1. Distribution of professional competency levels at the initial and final stages, %

At the final stage, the distributions of the experimental and control groups differed significantly: $\chi^2(2) = 21.057$; $p < 0.001$. A Cramer's V value of 0.239 indicates a small-to-moderate effect. The greatest contributions to the difference were the higher proportion at the high level and the lower proportion at the low level in the experimental group.

The experimental group's mean score was 2.428 (SD = 0.725; 95% CI [2.324, 2.532]), compared with 2.049 in the control group (SD = 0.821; 95% CI [1.930, 2.168]). The mean difference was 0.379 points and was statistically significant according to Welch's test: $t(360.45) = 4.700$; $p < 0.001$; 95% CI for the difference [0.221, 0.537]. The standardized effect size of $d = 0.489$ corresponds to a moderate practical effect.

In normalized form, the final indicator reached 80.93% in the experimental group and 68.31% in the control group. The between-group difference was 12.62 percentage points (95% CI [7.36, 17.88]). Relative to the initial stage, the indicator increased by 14.08 percentage points in the experimental group and by 2.91 points in the control group. The net gain, calculated as the difference between these changes, was 11.17 percentage points.

The principal results of the statistical tests are summarized in Table 3.

Table 3

Results of the between-group statistical comparison

Statistic	Initial stage	Final stage
χ^2 (df = 2)	0.347	21.057
p for χ^2	0.841	< 0.001
Cramer's V	0.031	0.239
Welch's t	0.522	4.700
df	367.64	360.45
p for t	0.602	< 0.001
Cohen's d	0.054	0.489

Taken together, the results allow rejection of the null hypothesis of no final between-group difference. Statistical significance should be interpreted jointly with the effect size and the substantive shift in competency levels: the experimental group demonstrated not only a higher mean score, but also a marked movement of students from the low and medium levels to the high level.

Discussion. The findings support the pedagogical value of an adaptive cycle in which diagnosis is directly connected to the content of the next task. When a student experienced difficulty calculating transformer efficiency or constructing a power balance, the system offered an additional theoretical unit and a practical activity of the corresponding type. Adaptation therefore did not simplify the curriculum; it selected the nearest appropriate learning step while preserving the shared professional objective.

The observed moderate effect is consistent with studies linking the effectiveness of digital personalization to the quality of the learner model, feedback, and pedagogical scenario [2; 6; 9]. A particularly important result is the 17.7-percentage-point reduction in the share of students at the low level in the experimental group. This suggests that the technology may provide the greatest benefit to students with pronounced baseline deficits by making their difficulties visible and offering additional opportunities for targeted practice.

At the same time, the mere presence of AI is not a sufficient condition for improved outcomes. The substantive validity of tasks depends on their alignment with professional actions, and the reliability of feedback depends on instructor participation. This conclusion is consistent with international recommendations emphasizing human-centeredness, transparency, and responsibility in the educational use of AI [4; 10; 15]. It also accords with the view that generative and analytical systems create both opportunities and risks that require pedagogical oversight [1; 5].

Learning analytics served a formative rather than punitive function in the described technology. The data were used to select tasks and discuss errors, but they did not replace a

comprehensive assessment of competence. This distinction is essential because a digital trace reflects only the part of student activity captured by the system. The project product, justification of an engineering solution, capacity to act in a new situation, and professional reflection all require expert interpretation [7-9].

The findings have several limitations. First, the quasi-experimental design cannot fully exclude the influence of differences among educational institutions, instructors, and regional conditions. Second, the analysis is based on aggregated distributions and therefore cannot account for individual trajectories or covariates. Third, the three-level scale simplifies the structure of professional competence. Fourth, the source data do not include a delayed follow-up assessment, so the durability of the effect cannot be established. Finally, the results relate to one field of study and should not be transferred automatically to other professional domains.

Further research should employ multilevel analysis of data from students and educational institutions, preregistered criteria, verification of assessment-rubric reliability, adjustment for baseline achievement, and comparison of different components of the technology. The persistence of the effect, its influence on student independence, and the balance between automated and instructor feedback also require separate investigation.

Conclusion. The study showed that the experimental and control groups were comparable at the initial stage: no statistically significant differences were found in either the level distribution or the composite score. After implementation of the AI-based adaptive educational technology, the experimental group demonstrated a more favorable level structure: 56.7% reached the high level compared with 36.1% in the control group, while 13.9% remained at the low level compared with 31.1% in the control group.

The final differences were confirmed by Pearson's chi-square test and Welch's t-test. The normalized indicator in the experimental group exceeded the control-group value by 12.62 percentage points; Cohen's $d = 0.489$ indicates moderate practical significance. The net gain relative to the initial stage was 11.17 percentage points.

The effectiveness of the technology arises from the combination of diagnostic accuracy, professionally oriented tasks, individualized feedback, and pedagogical interpretation of data. AI should be regarded as a tool that strengthens the instructor's work rather than replaces it. Further studies using individual-level data, control of contextual factors, and delayed measurement are required to confirm the durability and causal basis of the observed effect.

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