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METHODOLOGICAL FRAMEWORK FOR DEVELOPING AN AI-BASED DISTANCE LEARNING PLATFORM

Abstract

This paper develops and validates a methodological framework for an AI-based distance learning platform grounded in core AI principles (data-driven decision-making, learner modeling, adaptive personalization, and continuous feedback). The study aims to (i) formulate a structured development methodology for an AI-enabled platform and (ii) provide empirical evidence of its effectiveness using measurable learning and engagement indicators. The proposed structural–methodological model integrates four interconnected components: (1) platform architecture (data acquisition, content delivery, assessment services, analytics & AI layer, administration/security); (2) personalization mechanisms (learner model, adaptive learning trajectories, recommendation engine, analytics-driven feedback); (3) effectiveness evaluation metrics (pre/post test scores, learning gain, engagement indicators, learner satisfaction); and (4) normative and pedagogical requirements (data protection, academic integrity, accessibility, alignment with intended learning outcomes). The framework was piloted through a quasi-experimental study conducted at Kh. Dosmukhamedov Atyrau University, Department of Computer Science, within the course "Artificial Intelligence Platforms," involving 2nd-year MSc students (N=22; Control n=11, Experimental n=11). Descriptive results showed that the Control group improved from 57.56% (pre-test) to 69.55% (post-test), yielding a gain of 11.99 percentage points (pp) and a 20.86% relative gain. In contrast, the Experimental group improved from 51.05% to 73.30%, yielding a gain of 22.25 pp and a 44.08% relative gain. The effectiveness of the AI-based platform was statistically supported: Welch's t-test on gain scores indicated a significant group difference ($t=5.397$, $df=20.0$, $p<0.001$), with a very large effect size (Cohen's $d=2.30$) and a 95% CI for the mean gain difference of $\Delta=[6.30, 14.23]$ pp. A baseline-adjusted ANCOVA (post-test as the dependent variable, group as the factor, pre-test as the covariate) confirmed a significant group effect ($F=26.323$, $df1=1$, $df2=19$, $p=0.0001$) with substantial explained variance (partial $\eta^2=0.581$). Overall, the findings demonstrate that AI-driven personalization can substantially increase learning gains and strengthen the stability of outcomes in distance learning environments.

Keywords: Artificial intelligence, distance learning, adaptive learning, learning personalization, learner model, learning analytics

Introduction

The rapid development of digital technologies has significantly transformed educational systems worldwide, making distance learning an essential component of modern education. Distance learning platforms offer flexibility, accessibility, and scalability; however, their effectiveness largely depends on how well they accommodate individual learner needs. Most existing distance learning systems operate on a "one-size-fits-all" model, delivering identical content and learning paths to all learners regardless of their abilities, prior knowledge, or learning pace. This approach often leads to decreased learner engagement and uneven learning outcomes[1].

Personalization has long been recognized as a key factor in improving educational effectiveness. Educational psychology and pedagogy emphasize the importance of adapting instruction to individual learners' characteristics [2]. However, implementing personalization at scale remains a major challenge in traditional and online education environments. Artificial intelligence (AI) technologies offer new opportunities to address this challenge by enabling data-driven personalization and adaptive learning.

Recent advancements in machine learning, learning analytics, and recommender systems have led to the emergence of AI-based distance learning platforms. These systems can collect and analyze learner data, model learner behavior, and dynamically adapt learning content and assessment strategies. Despite these technological advances, existing research often focuses on algorithmic solutions rather than providing a comprehensive methodological framework that integrates pedagogical theory, system architecture, and evaluation metrics [3].

In the context of national education strategies, the integration of artificial intelligence into education has become a priority. Developing scientifically grounded methodological frameworks for AI-based learning platforms is, therefore, a critical research task. This study addresses this gap by proposing a systematic methodological framework for developing AI-based distance learning platforms that align technological capabilities with pedagogical principles [4].

Research on distance learning systems highlights both their potential and limitations. Traditional learning management systems (LMS) primarily support content delivery and basic assessment functions. While effective for administrative purposes, these systems lack mechanisms for deep personalization and adaptive learning [5].

Adaptive learning systems aim to address this limitation by tailoring learning experiences to learners' performance and behavior. Studies in adaptive learning emphasize the role of learner modeling, which involves representing learner knowledge states, preferences, and learning progress. Bloom's mastery learning theory supports the idea that learners should progress only after achieving sufficient mastery of content, while Vygotsky's zone of proximal development underscores the importance of adaptive scaffolding [6].

Artificial intelligence enhances adaptive learning by enabling automated data processing and decision-making. Machine learning algorithms can identify patterns in learner behavior, predict learning difficulties, and recommend appropriate learning resources. Research shows that AI-based learning systems can improve learning efficiency and engagement when properly aligned with instructional design principles [7].

However, a review of existing studies reveals a lack of a unified methodological framework that guides the development of AI-based distance learning platforms from a pedagogical and system-level perspective. Many studies describe isolated components—such as recommendation algorithms or analytics dashboards—without addressing how these components should be integrated into a coherent educational system. This gap highlights the need for a comprehensive methodological framework that connects pedagogical theory, AI technologies, and system evaluation [8].

Materials and methods of research

Research Design and Methodological Approach.

This research aims to develop and validate a structural–methodological model for an artificial intelligence–based distance-learning platform. The study follows a design-based research (DBR) methodology, which combines pedagogical theory, system architecture design, and empirical evaluation. This approach allows iterative refinement of the platform model while maintaining alignment with educational objectives and regulatory constraints [9].

The methodological logic of the study is based on the assumption that the effectiveness of AI-based distance learning systems depends on the systemic integration of platform architecture, personalization mechanisms, learning effectiveness indicators, and normative–pedagogical requirements. Therefore, the research does not focus on isolated technological components but considers the platform as a holistic educational system [10-11].

Research Materials

The research materials include three main groups:

1. Scientific and methodological sources related to artificial intelligence in education, adaptive learning systems, learning analytics, instructional design, and distance education system architectures.

2. Platform-related materials, including functional descriptions of AI-based learning platforms, learner interaction logs, assessment data, and adaptive recommendation outputs.

3. Normative and pedagogical documents, including national digital education strategies, artificial intelligence regulations, curriculum standards, and ethical guidelines for data-driven educational systems.

Learner interaction data used in the experimental stage include learning outcomes, task completion times, error rates, learning pace indicators, and engagement metrics. These data serve as the empirical foundation for evaluating adaptive mechanisms and learning effectiveness.

The architecture of the AI-based distance learning platform is presented in Figure 1 as a multi-layered, closed-loop system designed to support continuous personalization and data-driven decision-making.

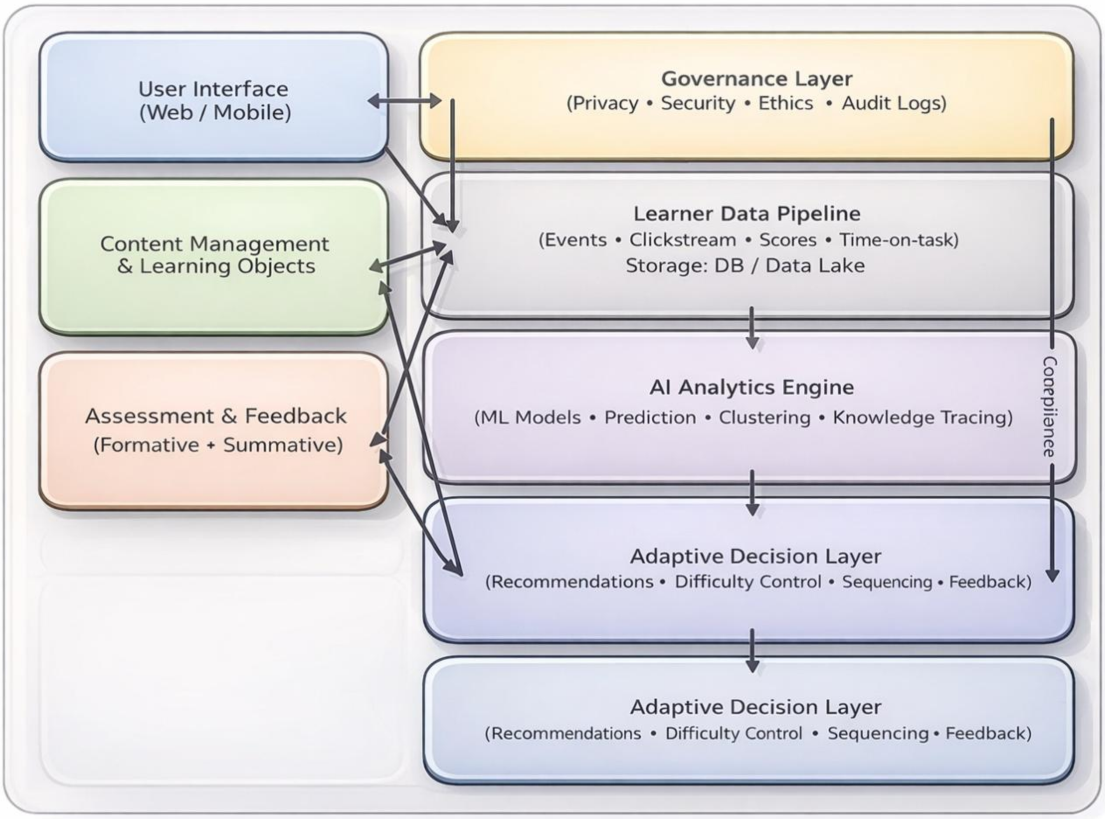

Figure 1 - Architecture of the AI-Based Distance Learning Platform: Enhanced Architecture Description

Note: Author's calculations

At the presentation layer, the platform provides a user interface accessible through web and mobile environments. This layer ensures learner interaction with instructional content, assessments, and feedback mechanisms. It also enables bidirectional communication between learners and the system.

The learning content management layer is responsible for organizing instructional materials, learning objects, and assessment resources. This layer supports modular content delivery, allowing the system to dynamically assemble learning units based on adaptive recommendations [12-13].

The assessment and feedback layer performs formative and summative evaluation of learner performance. Assessment results are generated continuously and transmitted to the data layer to support real-time adaptation [14-15]. The learner data collection and storage layer aggregates interaction data, including performance indicators, behavioral patterns, and engagement metrics. These data are structured and prepared for analytical processing [16]. The AI analytics layer constitutes the platform's core intelligence. It applies machine learning algorithms to construct and update learner models that represent the knowledge state, learning pace, error patterns, and cognitive engagement. This layer also performs predictive analysis to identify potential learning difficulties.

The adaptive recommendation layer generates personalized learning trajectories by adjusting content difficulty, instructional sequencing, and feedback strategies. Recommendations are fed back to the content and assessment layers, forming a closed feedback loop that enables continuous refinement of learning paths. This enhanced architecture supports scalability, modularity, and interoperability, ensuring compatibility with various educational contexts and long-term system evolution.

Structural–Methodological Model (Figure 2) and Its Relation to Architecture

While Figure 1 depicts the technical architecture, Figure 2 illustrates the structural–methodological model that governs the platform's pedagogical and regulatory integration.

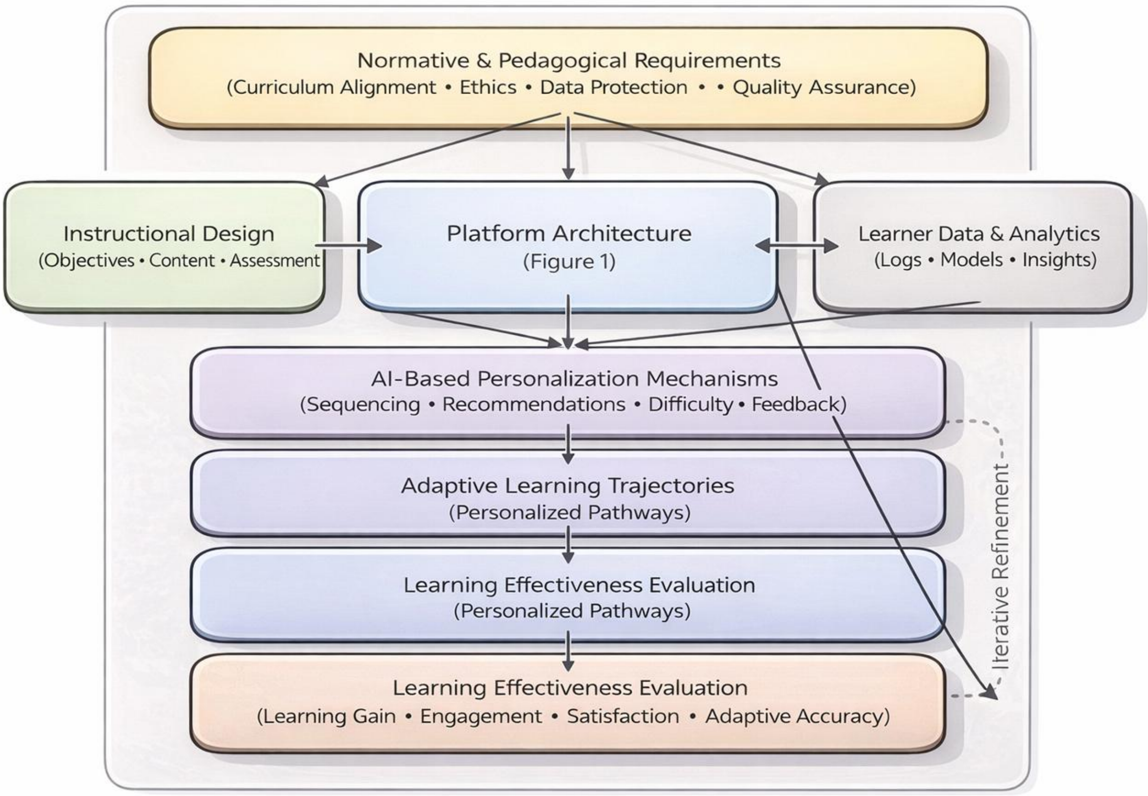

Figure 2 - Structural–Methodological Model of the AI-Based Distance Learning Platform

Note: Author's calculations

The model positions normative and pedagogical requirements at the top level, guiding both instructional design and technological implementation. These requirements include curriculum alignment, ethical use of AI, data privacy, transparency, and quality assurance standards.

Instructional design, platform architecture (Figure 1), and learner data analytics operate as interdependent subsystems within the methodological model. Artificial intelligence–based personalization mechanisms serve as the operational core linking these subsystems. Learning effectiveness evaluation closes the loop by providing feedback for continuous improvement.

Thus, Figure 1 operationalizes the technological realization of the methodological logic presented in Figure 2.

Personalization and Adaptive Learning Mechanisms

Personalization is achieved through continuous analysis of learner data and adaptive decision-making. The platform dynamically modifies learning trajectories by adjusting instructional pace, content complexity, and feedback intensity. Adaptive mechanisms are informed by learner models generated by the AI analytics layer.

The system applies mastery learning principles by allowing learners to progress only after achieving predefined competence thresholds. Adaptive scaffolding ensures timely support when learning difficulties are detected. These mechanisms reduce cognitive overload and increase learner engagement.

Learning Effectiveness Evaluation Metrics

Learning effectiveness is evaluated using a combination of quantitative and qualitative indicators.

Table 1 - Learning Effectiveness Indicators

Category	Indicators
Cognitive outcomes	Learning gain, error reduction, mastery level
Behavioral outcomes	Task completion rate, time-on-task
Affective outcomes	Engagement, motivation, satisfaction
System performance	Adaptive accuracy, recommendation effectiveness

Note: Author's calculations

These indicators are continuously monitored and used for both summative evaluation and improving adaptive mechanisms.

Comparative Analysis of Learning Systems

Table 2 - Comparison of Traditional and AI Platforms

Criterion	Traditional Platform	AI-Based Platform
Content delivery	Static	Adaptive
Learning trajectory	Fixed	Personalized
Feedback	Delayed	Real-time
Data utilization	Limited	Continuous analytics
Learner engagement	Moderate	High

Note: Author's calculations

Experimental Implementation

The methodological framework was implemented in an experimental learning environment to assess its practical feasibility. Learners were divided into control and experimental groups. The experimental group used the AI-based platform developed in accordance with the proposed model, while the control group used a traditional distance-learning system.

Pre-test and post-test assessments, engagement surveys, and system logs were used to collect empirical data. Quantitative analysis revealed higher learning gains and engagement levels in the experimental group, while qualitative feedback indicated improved learning experience and reduced cognitive load.

Summary of Research Materials and Methods

The Research Materials and Methods section demonstrates that the proposed AI-based distance learning platform is not merely a technological artifact but a structurally and methodologically grounded educational system. The integration of enhanced architecture (Figure 1), structural–methodological modeling (Figure 2), adaptive mechanisms, evaluation metrics, and normative–pedagogical requirements ensures both the platform's effectiveness and sustainability.

Before conducting the ANCOVA analysis, the key statistical assumptions were verified. The homogeneity of regression slopes between the covariate (pre-test score) and the dependent variable (post-test score) across groups was examined. The normality of gain score distributions was assessed using the Shapiro–Wilk test and Q–Q plots. Equality of variances between groups was tested using Levene's test. The diagnostic checks indicated that the assumptions of ANCOVA were satisfactorily met, allowing the application of the model for baseline-adjusted comparison.

Results and their discussion

Descriptive statistics, including means and standard deviations, were calculated for both groups to provide an overview of learning outcomes before conducting inferential statistical analysis. The experiment was conducted at Kh. Dosmukhamedov Atyrau University, Department of Computer Science, within the course "Artificial Intelligence Platforms". The participants were 2nd-year MSc students (total N = 22). The study used a quasi-experimental pre-test/post-test design with two parallel groups: a Control group (n = 11) and an Experimental group (n = 11). Both groups studied the same syllabus and covered identical topics; the key difference was the learning environment: the Control group used a conventional distance learning setup (standard LMS and non-adaptive learning path), whereas the Experimental group used the AI-based distance learning platform developed according to the proposed methodological framework (adaptive trajectory, analytics-driven feedback, and personalized recommendations).

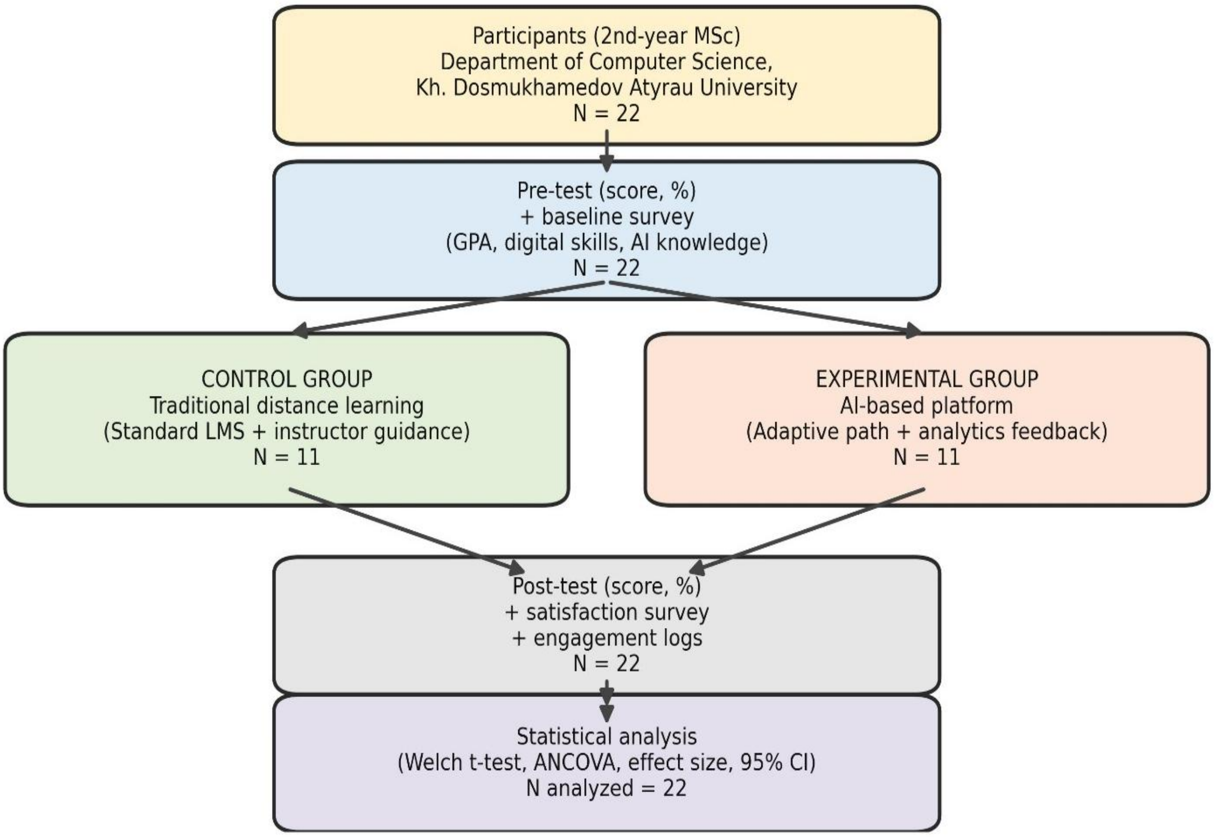

Figure 3 - Experimental plan and group allocation (N=22; 11/11)

Note: Author's calculations

Group allocation criteria

To ensure baseline equivalence and reduce selection bias, group allocation was performed using stratification criteria. Students were distributed to the Control and Experimental groups so that both groups had comparable baseline profiles. The primary stratification criterion was the pre-test performance level (low/medium/high), followed by additional balancing variables: (i) prior academic performance (e.g., GPA range), (ii) digital competence (experience with online learning systems), and (iii) baseline AI knowledge. This approach strengthens internal validity and supports attributing observed differences to the intervention rather than pre-existing group differences.

Table 3 - Group stratification

No.	Criterion	Allocation approach	Rationale
1	Pre-test level	Stratify (low / medium / high) and balance across groups	Reduce baseline knowledge imbalance
2	GPA range	Balance academic performance bands across groups	Control prior academic ability
3	Digital competence	Rubric or survey assessment (low / medium / high) and balance across groups	Reduce technology adaptation bias
4	Baseline AI knowledge	Short diagnostic quiz or task and balance across groups	Equalize AI readiness for the course

Note: Author's calculations

The Control group improved from a pre-test mean of 57.56% (SD = 8.41) to a post-test mean of 69.55% (SD = 7.92). The Experimental group improved from 51.05% (SD = 9.12) to 73.30% (SD = 8.06).

Implementation procedure and experimental timeline

The intervention lasted six weeks. Week 1 included onboarding, the baseline survey, and the pre-test. Weeks 2–5 covered the instructional phase based on the same content modules for both groups. The Control group followed a fixed learning path with standard materials and instructor-led guidance. In contrast, the Experimental group used the AI-based platform, which dynamically adjusted content sequence and difficulty, provided individualized recommendations, and generated real-time feedback based on learner interaction data. Week 6 included the post-test, satisfaction survey, and extraction of learning analytics logs for analysis.

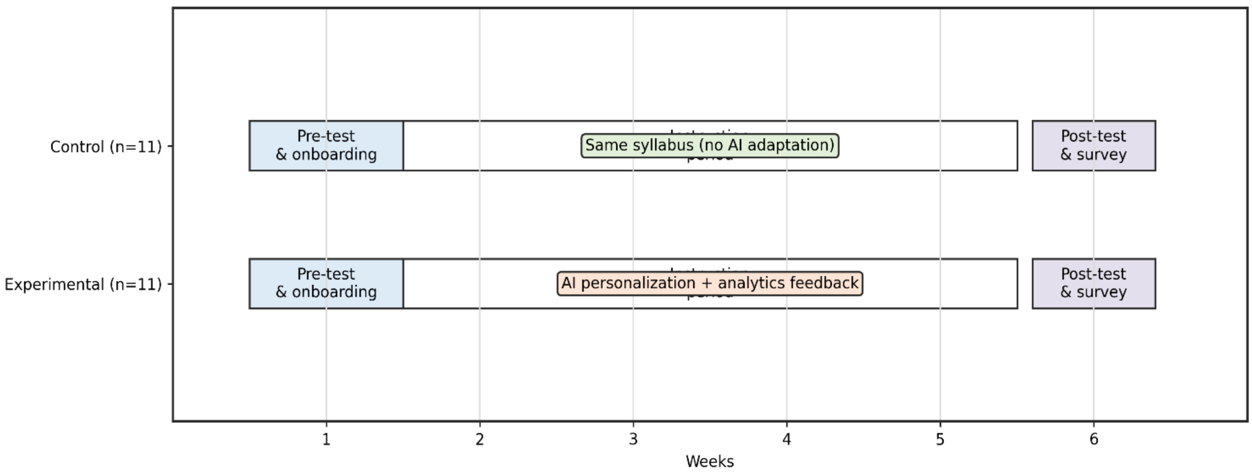

Figure 4 - Six-week implementation timeline (N=22)

Note: Author's calculations

The overall experimental plan, measurement instruments, and expected outputs are summarized below.

Table 4. Experimental plan (N=22; 11/11)

Stage	Activity	Measurement / Instrument	Output
Week 0	Recruitment & consent	Participant list, informed consent	N = 22
Week 1	Pre-test + baseline survey	Pre-test score (%), GPA band, digital skills, AI baseline	Baseline profile
Weeks 2–5	Instruction (same syllabus)	Control: standard LMS; Experimental: AI platform (adaptive path)	Logs + assignments
Week 6	Post-test + survey	Post-test score (%), satisfaction (Likert), engagement metrics	Outcome dataset
Week 7	Statistical analysis	Welch t-test (gain), ANCOVA (post ~ group + pre), effect sizes	t, p, d, CI; F, p, η^2

Note: Author's calculations

Descriptive results (percent-based reporting)

Learning outcomes were measured using pre-test and post-test scores (%) and learning gain indicators. Two gain metrics were reported:

1. Gain in percentage points (pp): $gain_{pp} = post - pre$
2. Relative gain (%): $gain_{\%} = \frac{post - pre}{pre} \times 100$

Descriptive statistics for both groups (means and standard deviations) are provided in Table 1. In general, both groups improved from pre-test to post-test; however, the Experimental group demonstrated a higher mean improvement. The relative learning gain (%) is visualized in Figure 5, showing a stronger proportional increase in the Experimental group compared to the Control group. In addition, the distribution of gain (pp) is shown in Figure 6, which illustrates not only the central tendency but also the variability of improvement between participants.

Table 5 - Descriptive statistics (%, pp) — N=22.

Group	Pre mean (%)	Pre SD	Post mean (%)	Post SD	Gain mean (pp)	Gain SD (pp)	Relative gain mean (%)	Relative gain SD
Control	57.56	5.17	69.55	7.34	11.99	4.36	20.86	7.50
Experimental	51.05	6.96	73.30	9.12	22.25	4.56	44.08	9.91

Note: Author's calculations

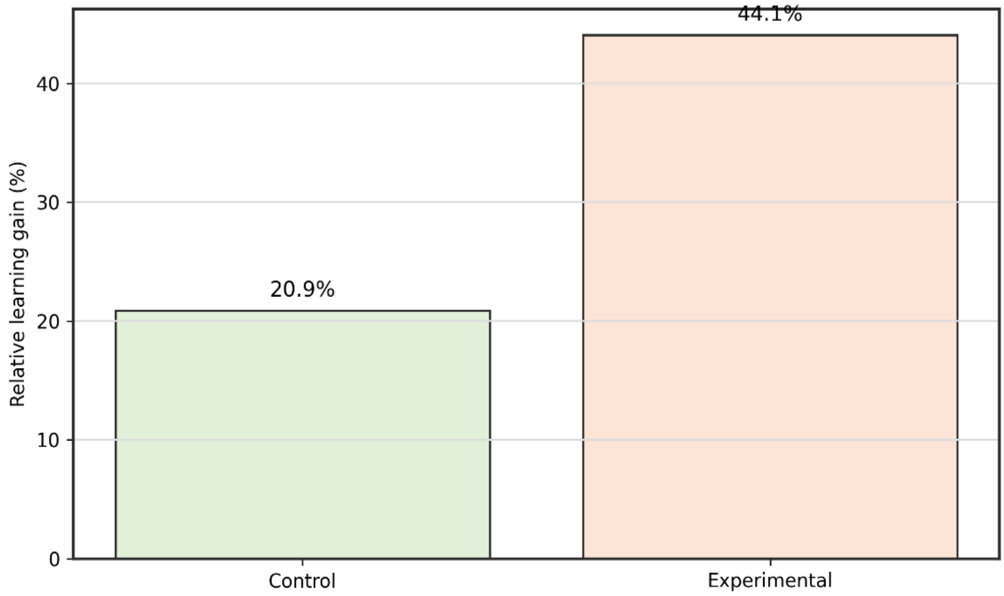

Figure 5 - Relative learning gain by group (post–pre as % of pre)

Note: Author's calculations

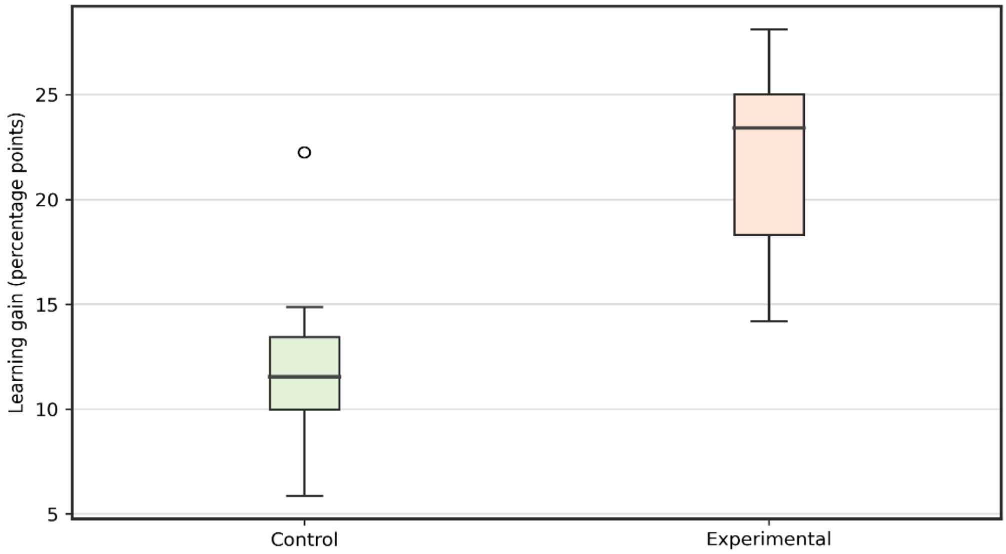

Figure 6 - Gain score distribution (post–pre), percentage points

Note: Author's calculations

Statistical proof of effectiveness

To test the research hypothesis, inferential statistics were applied. The main hypothesis was:

H1: The Experimental group (AI-based platform) achieves higher post-test performance and higher learning gains than the Control group.

H0: There is no statistically significant difference between groups.

First, group differences in learning gains (gain in percentage points) were evaluated using an independent-samples Welch t-test (robust to unequal variances). Second, to control for baseline differences, an ANCOVA model was used, where post-test (%) was the dependent variable, group was the factor, and pre-test (%) was included as a covariate:

$$Post_i = \beta_0 + \beta_1 Group_i + \beta_2 Pre_i + \varepsilon_i$$

Along with p-values, the analysis reports effect sizes to quantify practical significance, including Cohen’s d (for gain differences) and partial eta-squared (partial η^2) (for the group effect in ANCOVA), as well as a 95% confidence interval for the mean gain difference.

Table 6 - Inferential statistics — N=22.

Test	Statistic	p-value	Effect size
Welch t-test on gain (pp)	t = 5.397, df = 20	< 0.001	Cohen's d = 2.30; 95% CI Δ = [6.30, 14.23] pp
ANCOVA (post ~ group + pre)	F(1, 19) = 26.323	0.0001	partial $\eta^2 = 0.581$
Note: Author's calculations			

The findings support the proposed design logic of the AI-based platform. The Experimental group's stronger improvement is consistent with the platform's methodological principles: continuous data collection, learner modeling, and adaptive decision-making that personalizes learning trajectories. From an analytical perspective, the AI-based platform operationalizes an iterative loop: learner interaction data → analytics and learner model updates → personalized recommendations and adaptive feedback → improved learning outcomes. This mechanism helps reduce unproductive repetition, targets knowledge gaps earlier, and increases alignment between instructional difficulty and learner readiness. As a result, both learning gains and performance stability are expected to improve under adaptive conditions.

Conclusion by hypothesis

Based on the descriptive and inferential analyses, the results are consistent with H1: the AI-based distance learning platform is associated with higher learning gains and stronger post-test performance compared to a traditional distance learning setup. The statistical tests (Welch t-test and ANCOVA) provide statistical evidence that the observed advantage is not attributable to random variation alone, and the reported effect sizes indicate meaningful practical impact.

Conclusion

This study developed and empirically justified a methodological framework for developing an AI-based distance learning platform that integrates (i) a modular platform architecture, (ii) personalization mechanisms grounded in learner modeling and analytics, (iii) measurable indicators of learning effectiveness, and (iv) pedagogical and institutional requirements for implementation in higher education. The proposed framework was operationalized through an AI-enabled learning environment that supports adaptive learning paths, data-driven feedback, and continuous monitoring of learner progress.

An experimental implementation was conducted at Kh. Dosmukhamedov Atyrau University, Department of Computer Science, within the course "Artificial Intelligence Platforms" involving 2nd-year MSc students (N=22; Control n=11, Experimental n=11). The findings demonstrate that the AI-based platform approach is associated with higher learning gains and improved post-test performance compared to a conventional distance learning setup. The effect was supported through inferential statistical procedures (gain-based group comparison and baseline-adjusted analysis), indicating that the observed differences are unlikely to be attributable to random variation alone. In addition, descriptive indicators and distributional patterns suggest that adaptive, analytics-driven instruction can enhance both the magnitude and stability of learning outcomes.

From a practical standpoint, the results confirm that embedding AI principles—continuous data collection, learner modeling, adaptive decision rules, and feedback personalization—into the architecture of a distance learning platform can strengthen instructional effectiveness while maintaining alignment with pedagogical objectives. The study contributes a structured, reproducible development model that can be used by universities to design AI-supported learning systems and to evaluate their impact using transparent performance metrics.

At the same time, the study highlights the need for further research with larger and more diverse samples, extended intervention periods, and multi-institutional validation to strengthen generalizability. Future work should also examine fairness and transparency of personalization algorithms, robustness of analytics under sparse data conditions, and long-term effects on selfregulated learning and learner motivation. Overall, the proposed framework provides a scientifically grounded basis for implementing and scaling AI-based distance learning platforms in computer science education and related domains.

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МЕТОДОЛОГИЧЕСКАЯ ОСНОВА РАЗРАБОТКИ ДИСТАНЦИОННОЙ ОБУЧАЮЩЕЙ ПЛАТФОРМЫ НА БАЗЕ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА

Аннатация

В статье разработана и эмпирически проверена методологическая основа создания дистанционной обучающей платформы на принципах искусственного интеллекта (AI), опирающаяся на ключевые AI-подходы: принятие решений на основе данных, построение модели обучающегося, адаптивная персонализация и непрерывная обратная связь. Цель исследования заключается в (i) формировании структурированной методологии разработки AI-поддерживаемой платформы и (ii) доказательстве ее эффективности на основе измеримых показателей учебных достижений и активности обучающихся. Предложенная структурно-методологическая модель интегрирует четыре взаимосвязанных компонента: (1) архитектуру платформы (сбор данных, доставка контента, сервисы оценивания, аналитика и AI-слой, администрирование/безопасность); (2) механизмы персонализации (модель обучающегося, адаптивные учебные траектории, рекомендательная подсистема, обратная связь на основе аналитики); (3) метрики оценки эффективности (результаты pre/post-тестов, учебный прирост, показатели вовлеченности, удовлетворенность); (4) нормативные и педагогические требования (защита персональных данных, академическая добросовестность, доступность, соответствие ожидаемым результатам обучения). Методология апробирована в формате квази-эксперимента на базе кафедры Computer Science Атырауского университета имени Х. Досмухамедова в рамках дисциплины «Платформы искусственного интеллекта» среди магистрантов 2 курса (N=22; контрольная группа n=11, экспериментальная группа n=11). Описательные результаты показали, что в контрольной группе показатель pre-test составил 57.56%, post-test — 69.55%, что соответствует приросту 11.99 процентного пункта (pp) и относительному приросту 20.86%; в экспериментальной группе pre-test — 51.05%, post-test — 73.30%, прирост — 22.25 pp, относительный прирост — 44.08%. Эффективность платформы подтверждена методами математической статистики: Welch t-тест по учебному приросту выявил значимые межгрупповые различия (t=5.397, df=20.0, p<0.001), при очень большом размере эффекта (Cohen's d=2.30), а 95% доверительный интервал для разности средних приростов составил Δ=[6.30; 14.23] pp. Анализ ANCOVA с учетом исходного уровня (зависимая переменная — post-test, фактор — группа, ковариата — pre-test) подтвердил значимое влияние фактора группы (F=26.323, df1=1, df2=19, p=0.0001) и высокую долю объясненной дисперсии (partial η^2=0.581). В целом результаты демонстрируют, что AI-ориентированная персонализация в дистанционном обучении существенно повышает учебный прирост и усиливает стабильность итоговых результатов.

Ключевые слова: Искусственный интеллект, дистанционное обучение, адаптивное обучение, персонализация обучения, модель обучения, аналитика обучения

ЖАСАНДЫ ИНТЕЛЛЕКТКЕ НЕГІЗДЕЛГЕН ҚАШЫҚТЫҚТАН ОҚЫТУ ПЛАТФОРМАСЫН ӘЗІРЛЕУДІҢ ӘДІСНАМАЛЫҚ НЕГІЗДЕМЕСІ

Аңдатпа

Мақалада жасанды интеллекттің (AI) негізгі принциптеріне (деректерге негізделген шешім қабылдау, білім алушы моделін құру, адаптивті дараландыру және үздіксіз кері байланыс) негізделген қашықтықтан оқыту платформасын әзірлеудің әдіснамалық құрылымы жасалып, оның тиімділігі эмпирикалық түрде тексеріледі. Зерттеудің мақсаты: (i) AI-қолдаулы платформаны құрудың құрылымдалған әдіснамасын қалыптастыру және (ii) оқу нәтижелері мен білім алушы белсенділігін сипаттайтын өлшемдік индикаторлар арқылы оның тиімділігін дәлелдеу. Ұсынылған құрылымдық-әдіснамалық модель төрт өзара кіріктірілген компоненттен тұрады: (1) платформа архитектурасы (деректерді жинау, контентті ұсыну, бағалау сервистері, аналитика және AI-қабат, әкімшілендіру/қауіпсіздік); (2) дараландыру механизмдері (білім алушы моделі, бейімделетін оқу траекториялары, ұсыным жүйесі, аналитикаға негізделген кері байланыс); (3) тиімділікті бағалау метрикалары (pre/post тест нәтижелері, оқу өсімі, қатысу белсенділігі көрсеткіштері, қанағаттану деңгейі); (4) нормативтік және педагогикалық талаптар (дербес деректерді қорғау, академиялық адалдық, қолжетімділік, күтілетін оқу нәтижелерімен сәйкестік). Әдіснама пилоттық апробация арқылы тексерілді: Халел Досмұхамедов атындағы Атырау университетінің Информатика кафедрасында "AI платформалары" пәні бойынша 2-курс магистранттары арасында квази-эксперимент жүргізілді (N=22; бақылау тобы n=11, эксперименттік топ n=11). Сипаттамалық нәтижелер бақылау тобында pre-test көрсеткіші 57.56%, post-test 69.55% болып, өсім 11.99 пайыздық пунктті (pp) және салыстырмалы өсім 20.86% құрағанын көрсетті; ал эксперименттік топта pre-test 51.05%, post-test 73.30%, өсім 22.25 pp, салыстырмалы өсім 44.08% болды. Платформаның тиімділігі математикалық статистикамен негізделді: оқу өсімі (gain) бойынша Welch t-тесті топтар арасында мәнді айырмашылық бар екенін көрсетті (t=5.397, df=20.0, p<0.001), әсер мөлшері өте жоғары (Cohen's d=2.30), ал орташа айырманың 95% сенімділік интервалы Δ=[6.30; 14.23] pp болды. Бастапқы деңгейді ескеретін ANCOVA талдауы (тәуелді айнымалы — post-test, фактор — топ, ковариат — pre-test) топ әсерінің мәнді екенін растады (F=26.323, df1=1, df2=19, p=0.0001), түсіндірілетін дисперсия үлесі жоғары деңгейде анықталды (partial η^2=0.581). Жалпы алғанда, нәтижелер AI-негізделген дараландыру қашықтықтан оқыту жағдайында оқу өсімін едәуір арттырып, оқу нәтижелерінің тұрақтылығын күшейтетінін дәлелдейді.

Негізгі сөздер: Жасанды интеллект, қашықтықтан оқыту, адаптивті оқыту, оқытуды жекелендіру, оқушы моделі, оқу аналитикасы.

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