Methodological Framework for Designing AI-Based Distance Learning Platforms

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***Abstract*—Artificial Intelligence (AI) opens up new perspectives for the transformation of distance learning; however, there is still no clearly structured methodological framework for the development of effective AI-based learning platforms. This study proposes the framework model "learning behavior – AI-oriented scenarios", which aims to identify key pedagogical and technological factors that contribute to effective learning in a digital environment. Based on an analysis of the scientific literature in educational technologies and the use of AI in teaching, the main characteristics of learning behavior are identified: personalized goal setting, adaptive response to feedback, and autonomous engagement. These characteristics correspond to constructivist and experiential approaches to learning. The study examines how intelligent recommendation systems, adaptive content, and AI-based learning behavior analytics contribute to the development of these characteristics and enhance educational outcomes. As an example, a case study is presented on the development of a prototype AI platform for distance learning, whose effectiveness is supported by survey results demonstrating increased student motivation and engagement. The findings address three key research questions and contribute to the theoretical and methodological foundation for integrating AI into the design of distance education.**

***Keywords*—artificial intelligence, distance learning, learning behavior, adaptive scenarios, educational technologies**

I. Introduction

Modern Artificial Intelligence (AI) technologies open up new perspectives for distance learning, offering deeper and more personalized experiences [1]. However, many traditional online courses and educational platforms do not fully contribute to the formation of a conscious and reflective learning experience for students. Experiential learning theory offers an effective approach to addressing this problem, emphasizing the importance of gaining knowledge through practical experience and subsequent reflection [2]. In the context of distance education, students can construct their own understanding of the learning material through interactive interaction with the digital environment, adaptive tasks, and intelligent prompts [3].

AI significantly expands the possibilities of personalized and adaptive learning in an online environment. For example, intelligent recommendation systems adapt educational content to the individual needs of students, taking into account their level of training, learning style, and interests [4]. Natural language processing technologies provide real-time support, helping students formulate questions and receive context-based clarifications. In addition, visualization tools such as Augmented and Virtual Reality (AR/VR) contribute to an immersive educational experience, allowing students to delve deeper into learning scenarios [5].

In recent years, researchers have increasingly focused on studying how students' interaction with the digital environment and learning scenarios affects the effectiveness of distance learning. Research shows that various forms of activity—such as adaptive tasks, simulations, learning through role modeling, and scenario exercises—contribute to deeper knowledge acquisition and the development of reflective thinking [6]. Other works examine the impact of information presentation methods in a digital educational environment, including multimedia explanations, visual cues, chatbots, and explanatory annotations, on the comprehension of educational material and the formation of sustainable knowledge [7].

Although Kolb's model sets out the general principles of experiential learning, it does not fully reveal how contextual and technological factors influence the learning process in a digital environment [8]. This view has also been developed in distance learning studies, which emphasize that the effectiveness of educational experiences directly depends on situational factors such as interface design, feedback management, types of interaction between participants, access to intelligent support, and individual characteristics of students, including the level of digital literacy, motivation, and learning style [9].

Nevertheless, despite numerous studies conducted during the COVID-19 pandemic, there is still a lack of systematic comparison between fully online and blended (hybrid) learning formats in the context of modern AI-driven tools. Recent evidence suggests that blended learning often leads to higher academic performance and motivation, but its effects on engagement remain inconsistent across different cultural contexts [10]. A large-scale meta-analysis [11] confirmed that blended and flipped models significantly outperform traditional face-to-face instruction in terms of achievement and self-efficacy, while fully online models show only *modest* benefits. Furthermore, empirical studies demonstrate that blended learning may produce more sustainable outcomes in specific areas such as grammar acquisition [12].

This gap remains highly relevant in the post-pandemic era, as employers increasingly report weaker collaboration and communication skills among graduates of purely online programs (81.9%) compared to blended or face-to-face models (88.3%) [13]. Moreover, executive education trends indicate a persistent demand for blended approaches that combine flexibility with social interaction, even as AI, AR/VR, and adaptive feedback systems reshape digital pedagogy [14]. Therefore, renewed research attention is needed to assess how interactive and adaptive scenarios can enhance both online and blended learning models, ensuring not only academic success but also the development of critical professional and social competencies.

In this study, blended learning is defined as a structured integration of synchronous face-to-face sessions (30%) with asynchronous online modules (70%), supported by AI-driven adaptive tools. The face-to-face sessions focus on collaborative activities, discussions, and peer feedback, while the online modules provide personalized practice, simulations, and interactive scenarios. This structure allows us to systematically compare the impact of blended and fully online models on engagement and learning outcomes.

This study proposes a methodological framework for designing distance learning platforms based on artificial intelligence, drawing on the analysis of scientific literature. This model highlights key learning behavioral characteristics and examines how various digital and interactive scenarios contribute to their development. The empirical study, conducted using a prototype AI platform for distance learning, aims to explore how digital technologies and intelligent systems enhance experiential and personalized learning.

The research focuses on the following issues: **RQ1:** What are the key learning behavioral characteristics that contribute to effective learning in AI-oriented distance learning platforms?

RQ2: How do various interactive and adaptive scenarios affect the formation of these learning behavioral characteristics?

RQ3: Can a distance learning platform developed based on the proposed framework increase student engagement and learning effectiveness?

Solving these research issues will contribute to the theoretical understanding of the integration of AI into distance education, as well as offer practical recommendations on the design of adaptive digital learning environments.

II. Literature Review

In the context of AI-based distance education, the learning process is increasingly taking place in digital, adaptive, and personalized environments, where elements such as intelligent recommendations, real-time learning, interaction with chatbots, as well as visualization and analysis of progress play crucial roles. The Kolb model (Fig. 1) provides an important theoretical basis for understanding the educational process in the context of distance learning. However, considering the specifics of the digital educational environment and the rapid introduction of artificial intelligence, a deeper study of the mechanisms by which situational and technological factors influence the behavior and motivation of students is required. This includes analyzing the interactions between students and intelligent platforms, adapting content in real time, as well as designing individual learning paths. To effectively design AI-oriented educational solutions, it is necessary to develop a more holistic and flexible theoretical framework that takes into account both pedagogical principles and the capabilities of modern digital technologies.

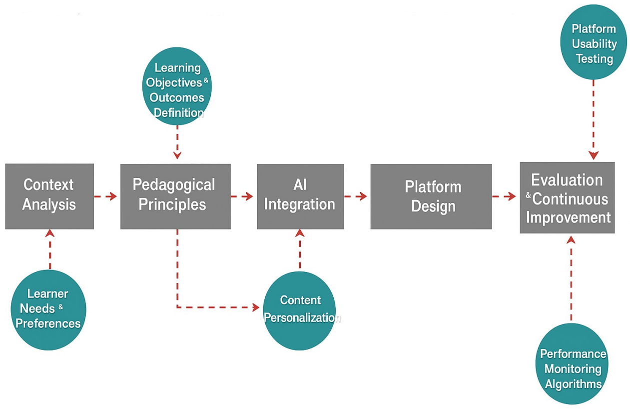

Fig. 1. Methodological framework for designing AI-based e-learning platforms.

The experience of AI-based distance learning provides unique opportunities for the formation of digital literacy, the development of metacognitive skills, and the personal growth of students [15]. Interactivity and active student participation in the learning process are recognized as key elements that strengthen experiential learning in digital educational environments [16].

In modern research, three main dimensions of effective AI-based distance learning are highlighted:

- Personalization—adapting content to individual needs and learning styles;
- Interactive engagement—ensuring active participation through simulations, case studies, chatbots, and real-time feedback;
- Digital interaction and knowledge sharing—encouraging collaboration, idea exchange, and the development of digital communication skills [17].

These dimensions, as the main components of an "AI-oriented educational environment," have a significant impact on the cognitive, social, and emotional development of students.

Recent research confirms the importance of personalization, digital engagement, and interactive sharing in building an effective learning experience. Thus, Bailey, D. shows that the value of a student's digital experience acts as a mediator between interaction with the platform and educational outcomes [18]. This indicates the need to refine classical learning models, such as the Kolb model, taking into account the specifics of the digital environment. Dirsehan, T. developed a scale of memorable digital experiences, structured similarly to the above three dimensions [19].

In addition, the quality of digital communication is becoming an important factor in successful distance learning. The greater the feeling of "distance" between the teacher, the platform, and the student, the lower the motivation and satisfaction among learners [20]. The lack of cultural and linguistic adaptation in an AI environment can lead to misunderstandings and negative attitudes. Therefore, it is extremely important to consider diversity and inclusivity, provide interpretive support and explanatory feedback, and help students perceive differences in educational experiences with openness and respect [21].

Despite the extensive opportunities provided by distance learning using artificial intelligence, not every digital educational experience leads to real learning outcomes. As Peters, O. point out, not every experience by itself guarantees learning, and the same digital environment can have different effects on different students [22].

Modern research takes into account both situational and individual factors that influence the success of learning in digital environments. From the point of view of the situational approach, real online learning unfolds in time and space, being shaped by the student's interaction with the digital platform, its interface, intellectual recommendations and the student's willingness to learn new material independently. The immediate digital environment — whether it's a virtual classroom, simulator, or intelligent assistant—plays an important role in shaping learning outcomes [23].

This approach emphasizes that personal development in the process of distance learning includes not only the acquisition of knowledge, but also the transformation of self-perception, confidence, attitude to learning and ideas about one's own role in the educational process. In addition, direct interaction with educational materials, active participation in digital tasks, as well as deep involvement in interaction with teachers, AI and other participants of the online course play an important role. All of this contributes to creating memorable and meaningful educational experiences that enhance learning and personal growth [24].

Individual factors also play a crucial role in the effectiveness of learning in the context of distance education based on AI. As noted by Nikitenko [25] the presence of a pronounced learning orientation in the student (the desire for independent development of new knowledge) positively correlates with the depth and quality of learning in a digital environment. This indicates that a purposeful approach and internal motivation significantly enhance the effect of interaction with educational AI platforms.

The use of digital learning tools such as intelligent assistants, adaptive tests, and interactive simulations further strengthens the positive impact of learning orientation on effectiveness. Kosinski, M. S. introduced the "digital researcher" scale, which evaluates parameters such as adaptability to the digital environment, openness to new experiences, and intrinsic learning ability in a digital context [26]. It was found that students with flexible thinking and a willingness to experiment in new educational environments demonstrate higher academic achievements. However, these parameters have limitations in predicting all aspects of distance learning potential, especially in an AI-oriented environment.

Although distance learning provides extensive opportunities for acquiring knowledge, they do not always translate into real educational outcomes, since the same digital content can have different effects on different learners [27]. Existing research seeks to identify elements that contribute to effective learning in an online environment, and thus form a useful basis for further analysis. However, there is still no systematic model that explains the factors that enhance learning in the context of distance learning platforms, especially given the growing integration of artificial intelligence technologies. The use of AI opens up new opportunities for personalization, interactivity, and adaptability of the educational process, but further research is needed to understand the mechanisms by which AI promotes in-depth and meaningful learning.

III. Materials and Methods

In order to deepen the understanding of how students master the material in the context of distance learning based on artificial intelligence, this study suggests a causal methodological framework, presented in Fig. 1. This framework makes it possible to identify the factors contributing to experiential learning by adapting the Kolb model to the digital educational space. It clarifies how three key learning behaviors—problem solving, critical reflection, and immersive interaction—directly influence the four stages of Kolb's cycle: concrete experience, reflective observation, abstract conceptualization, and active experimentation.

In addition, the framework describes how various digital learning scenarios—activity scenarios, information presentation scenarios, and digital interaction scenarios—affect these three key behaviors, thereby enhancing the educational effect of distance learning.

In particular:

- Activity scenarios (for example, interactive tasks, case studies) are designed to encourage students to find challenges and contribute to the formation of specific experiences.
- Information scenarios (personalized materials, visualizations, video analysis) provide rich knowledge, provoking critical reflection and facilitating reflective observation.
- Interaction scenarios (forums, AI feedback, group work) create an immersive and engaging environment, enhancing digital engagement and fostering deep educational engagement.

The proposed framework emphasizes that well-designed digital scenarios based on an AI distance learning platform not only enhance the learning experience, but also contribute to the development of students' metacognitive and personal competencies.

Designing tasks with an optimal level of complexity within the framework of AI-based distance learning deepens students' cognitive experience and supports the development of their personal and metacognitive qualities. Such tasks are closely related to the "concrete experience" and "active experimentation" stages in Kolb's experiential learning model. By actively engaging in solving complex problems, students gain a rich learning experience that initiates the learning cycle. In addition, while completing such tasks, they can apply previously acquired knowledge and adapt their behavioral strategies, which corresponds to the phase of active experimentation [28].

The desire to solve complex problems presupposes that students independently choose or participate in tasks of moderate complexity that create conditions for learning, self-assessment, and feedback [29]. This idea is based on the theory of goal setting and the theory of deliberate practice.

According to the first, clearly formulated and challenging goals motivate students to make greater efforts, develop resilience, and optimize task execution strategies. The second emphasizes that systematic practice with a well-chosen level of difficulty, combined with constant feedback, is a crucial prerequisite for the formation of expert skills.

Practice with an appropriate level of difficulty and constant feedback is the key to building professional skills. Educational tasks involving an intellectual challenge stimulate learning, because in situations where existing knowledge and strategies are insufficient, students have to develop new approaches to solving problems, which contributes to the growth of competenc [30].

According to the theory of transformative learning by Mezirow [31] such challenges can initiate critical reflection, encouraging students to reconsider their previous beliefs and attitudes, which, in turn, leads to a transformation of thinking and behavior change.

In an AI-oriented educational environment, designing tasks with moderate but stimulating complexity—for example, interactive simulations, logical tasks, or cases with multiple solutions—can create conditions for deep immersion that require maximum engagement and concentration. Such assignments help students gain a deeper understanding of the learning material through practice and trial action.

Kaptelinin [32] applying activity theory to the analysis of interactive user behavior in the museum environment, revealed that moderately complex tasks involving manual interaction and team problem solving contribute to the formation of new knowledge through practical interaction. Similarly, digital technologies open up new opportunities in distance learning: interactive tasks, VR quests, mind games, and adaptive tests increase motivation, maintain interest in learning, and enhance memorization.

Empirical research confirms that well-designed, interactive and moderately complex tasks can activate cognitive initiative, enhance immersion in the material, promote understanding and support the processes of building and transferring knowledge. At the same time, three components are critically important:

1) commensurate complexity of the task,
2) built-in reflection,
3) prompt and constructive feedback.

In addition, the digital learning environment should be safe and error-tolerant in order to encourage students to experiment, maintain motivation to learn, and guide them through the stages of concrete experience and active experimentation, thereby developing their metacognitive and professional competencies.

To empirically test the proposed framework, the study involved 120 undergraduate students from Kh. Dosmukhamedov Atyrau University**.** Participants were randomly assigned into two groups: an experimental group, which studied with the support of an AI-based distance learning platform, and a control group, which relied on traditional digital tools. Prior to data collection, the research instruments (questionnaires and tasks designed according to the Kolb cycle and goal-setting principles) were validated for reliability and internal consistency. This ensured methodological transparency and provided a solid basis for testing the stated hypotheses.

Hypotheses for distance learning with AI:

1) The desire to perform complex tasks has a positive effect on the formation of a specific learning experience.
2) The desire to complete difficult tasks has a positive effect on active experimentation in the learning process.

IV. Research Results

As an applied case for testing the developed methodological framework for experiential learning in an AI-based distance learning environment, the virtual educational space "Digital AI Campus" was chosen, which was specifically designed for students of pedagogical and technical fields. This digital campus simulates elements of a real educational environment: online labs, interactive seminars, learning situation simulations, and artificial intelligence assistants.

As illustrated in Fig. 2, the cycle of learning experiments and its tools clearly demonstrates how such AI-based platforms support the integration of practical, reflective, and interactive components of the educational process.

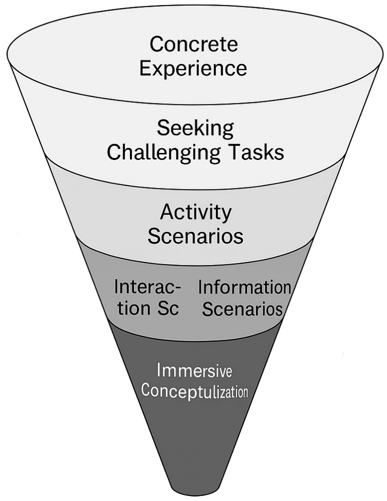

Fig. 2. A cycle of learning experiments and its tools in AI-based distance learning platforms.

The AI Digital Campus offers a rich range of resources for active and meaningful interaction. Students can participate in project activities, work with intellectual cases, receive feedback from an automated assessment system, and interact with teachers and other participants through simulations and VR tools. All this aligns with the proposed framework of experiential learning, emphasizing active participation, reflection, and knowledge construction in the process of interacting with the context.

Nevertheless, the implementation of digital learning with AI faces a number of challenges. Currently, most online courses remain linear and reproductive, which limits students' ability to actively immerse themselves in learning situations and develop critical thinking. In addition, teaching materials are often fragmented, lack a coherent narrative structure, and do not provide cognitive connectivity between modules.

To overcome these problems, this study proposes an interactive educational platform based on an experiential learning framework. Such a platform will include:

- Adaptive information delivery mechanisms that organize knowledge into a logically connected and pedagogically

consistent structure;
- Interactive learning scenarios aimed at involving students in problem-solving and modeling real-world practice situations;
- An instant feedback system supported by AI, promoting reflection and enabling the creation of new knowledge based on prior experience.

The platform aims to create a structured, interactive environment that encourages users to actively explore the learning material. The main interface of the platform is a visual map of the digital educational space, as shown in Fig. 3. This map shows the structural organization of the content and the distribution of key educational modules. A clear visual design helps students quickly form an overview of the course, establish an initial cognitive framework, and create the basis for further in-depth study.

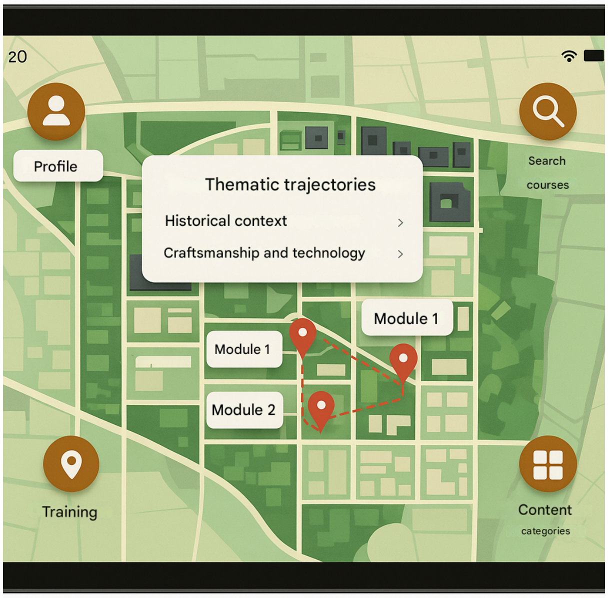

Fig. 3. Interface prototype illustrating adaptive thematic learning trajectories in the ai-based e-learning platform.

Four functional icons on the main screen correspond to the main modules of the platform: “Profile”, “Course Search”, “Thematic Trajectories,” and “Content Categories.” The Profile section provides personalized management options: setting preferences, viewing progress, course history, and adapting to the individual needs of the user. The Course Search feature supports both text search and an AI-based recommendation engine, meeting the demand for both targeted and recommended learning.

The Thematic Trajectories module offers two learning paths: Historical Context and Mastery and Technology, focusing respectively on the history of the subject area and applied aspects. Each path includes several modules structured around the principles of adaptive learning, where tasks and information blocks systematically guide the user through the topic. The Content Categories section provides structured access to educational resources, helping form a clear knowledge structure.

The functionality of the “adaptive thematic route” corresponds to the key learning behavior identified in this study: the ability to solve complex problems. The AI-based distance learning platform offers several individualized learning paths, such as “algorithmic thinking” or “user interface design,” each of which includes a sequence of modules united by a common theme and designed to develop research-oriented, goal-directed learning.

This approach is based on the theory of purposeful practice by Van Der Vleuten, C. P., according to which the consistent performance of moderately complex, focused tasks with constant feedback fosters the effective development of professional competencies [33].

For example, the “algorithmic thinking” route begins with an overview module, in which users are provided with information about the topic, the number of tasks, the expected completion time, and the target learning outcomes (Fig. 4). This helps the student quickly build a cognitive understanding of the educational task. Next, the system visualizes the sequence of modules in the form of an interactive map that highlights completed and active tasks, encouraging step-by-step learning of the material.

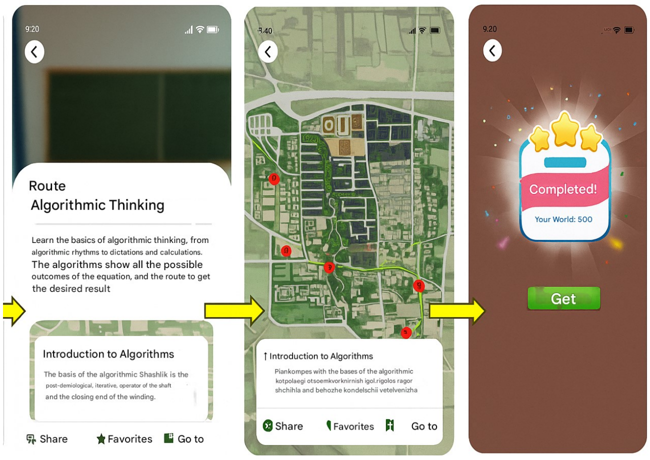

Fig. 4. The “Algorithmic Thinking” adaptive learning route: from introduction, through interactive map of tasks, to gamified completion feedback.

The tasks of each route are designed in accordance with goal-setting theory, according to which clear and moderately complex goals enhance intrinsic motivation and cognitive engagement [34]. Each module contains detailed instructions and evaluation criteria, helping students understand expected outcomes and guiding them to purposefully master the material.

After successfully completing all the modules of the route, the AI-based system provides personalized feedback and rewards (in the form of points, badges, or recommendations), encouraging achievement and supporting continued learning. Such an immediate feedback mechanism helps sustain motivation, consolidate acquired knowledge, and build a solid knowledge structure.

The assessment stage is aimed at verifying the effectiveness of the distance learning platform developed on the basis of the methodological framework in improving the quality of students’ educational experience. As part of the quasi-experimental design, a questionnaire survey was conducted to compare results between two groups of students. Table 1 contains a list of scales and sources used in the compilation of the questionnaire.

To ensure the reliability and validity of the questionnaire, content validity was established through expert review, construct validity confirmed via exploratory factor analysis (KMO = 0.82, Bartlett’s test $p < 0.001$), and reliability confirmed with Cronbach's α = 0.84–0.91. As part of the quasi-experimental design, a questionnaire survey was conducted to compare the results between the two groups of students. Table 1 contains a list of scales and sources used in the compilation of the questionnaire.

Table 1. Kolb's model in the context of AI distance learning

Stage	An analog in an AI environment	Application example
Concrete Experience (CE)	Interaction with digital content (videos, simulations, AR/VR)	A student uses a virtual laboratory simulator
Reflective Observation (RO)	Automatic analytics, AI feedback, self-assessment	AI indicates the mistakes made
Abstract Conceptualization (AC)	Personalized generalization using AI	The system generates summaries and diagrams based on student actions
Active Experimentation (AE)	Completing new tasks suggested by the system	The student receives an adapted task of increased complexity

Working definitions of the constructs were applied: satisfaction was defined as the learner's subjective evaluation of enjoyment, usability, and expectations; learning effectiveness as the degree of improvement in knowledge, skills, and competencies; engagement as cognitive, emotional, and behavioral investment in learning tasks; and technology adoption as perceived ease of use and usefulness, based on the TAM model.

The study involved 60 students selected from universities with a technical and pedagogical profile, who were divided into two comparable groups of 30 people each. The experimental group used a developed platform with AI components (personalized learning, adaptive routes, recommendations), while the control group studied using traditional online courses without AI support.

The questionnaire consisted of three sections, as shown in Table 1.

1) User Profile,
2) Digital learning Experience,
3) Technology Acceptance (based on the TAM — Technology Acceptance Model).

Both groups received training on the same topics for the same period of time, after which they filled out an online questionnaire using the Likert scale with five gradations. As a result, 60 valid responses were collected.

To identify the differences between the two groups, t-tests were conducted for independent samples aimed at analyzing differences in the main parameters:

- perception of educational value,
- involvement in learning,
- convenience and satisfaction,
- adoption of AI technology.

In addition, effect sizes (Cohen's d) were calculated for each comparison to estimate the magnitude of the observed differences.

Effect sizes were calculated for each t-test. Cohen's d ranged from 0.95 to 1.20, indicating large effects. For example, the difference in learning effectiveness (LER1) between groups yielded $d = 1.12$. A post-hoc power analysis ($N = 60$, $\alpha = 0.05$) confirmed statistical power > 0.95 for all comparisons, ensuring robust detection of true differences.

The results demonstrated the contribution of the developed platform to improving the effectiveness of distance learning and confirmed the importance of including AI in the educational process.

Table 2. A test of independent samples between the control and experimental groups

Indicator	The average value		T- meaning	P- meaning	Effect size (d)
	The experimental group	The control group			
UIQ1—User-friendliness of the interface	4.40	3.05	6.890	0.002	1.05
UIQ2—AI-based personalization	4.55	2.90	7.120	0.001	1.12
UIQ3—Easy navigation	4.43	3.00	6.740	0.002	1.12
LER1—Learning effectiveness	4.60	3.15	6.980	0.001	1.08
LER2—Time management support	4.47	3.10	6.520	0.003	1.10
LER3—Motivation of students	4.50	3.05	6.410	0.003	1.07
AIA1—Adaptive assessment	4.43	3.00	6.590	0.002	1.09
AIA2—Real-time feedback	4.48	2.95	6.670	0.002	1.10
AIA3—Predicting student errors	4.35	3.05	5.900	0.006	1.02
UX1—Engagement	4.55	3.20	6.710	0.002	1.08
UX2—Satisfaction	4.42	3.00	6.850	0.001	1.11
UX3—Trust in the platform	4.40	3.05	6.200	0.004	1.05

As part of the study, t-tests were conducted to compare the differences between the control and experimental groups in a number of areas reflecting generalized educational outcomes and technology adoption.

Participants in the experimental group using an artificial intelligence-based distance learning platform showed higher averages in the following areas: knowledge and understanding, attitudes and values, activity and progress, skill development, as well as engagement, inspiration and creativity.

The results of independent t-tests showed statistically significant differences between the two groups in all of these indicators (see Table 2), which confirms the effectiveness of the AI-based platform in improving the educational experience of students.

Students in the experimental group highly appreciated the platform in terms of perceived ease of use and usefulness. They noted that the system is intuitive, easy to learn, and practical to apply. The interface was recognized as user-friendly, and the platform was considered to reduce cognitive load and increase motivation.

In addition, the students pointed out that the AI platform effectively supports the learning process, increases awareness, and facilitates comprehension of educational material. These results demonstrate the success of design solutions in the field of UX design and are consistent with the quantitative data presented in Table 3. To provide a clearer visualization of the main results, Fig. 5 and Fig. 6 present comparative bar charts of the experimental and control groups across the main indicators. Fig. 5 summarizes the learning experience indicators (UIQ, LER, AIA, UX), while Fig. 6 shows the indicators of technology adoption (LP, PP). These visualizations highlight the significant differences between the groups and confirm the statistical results presented in Tables 2 and 3.

Table 3. Test of independent samples between control and experimental groups (technology adoption)

Indicator	The average value		T- meaning	P- meaning	Effect size (d)
	The experimental group	The control group			
LP1—Ease of learning the interface	4.40	2.85	6.782	0.002	1.03
LP2—Ease of navigation	4.45	2.90	5.015	0.018	0.91
LP3—Intuitive operation	4.25	4.10	2.345	0.045	0.52
PP1—Usefulness for the learning process	4.30	2.80	5.602	0.009	0.95
PP2—Improving the effectiveness of training	4.20	3.10	4.512	0.030	0.84
PP3—The overall usefulness of the platform	4.35	3.00	5.321	0.012	0.90

Note: $p < 0.05$, $*p < 0.01$, $**p < 0.001$. *LP*—"Ease of use"; *PP*— "Perceived usefulness"

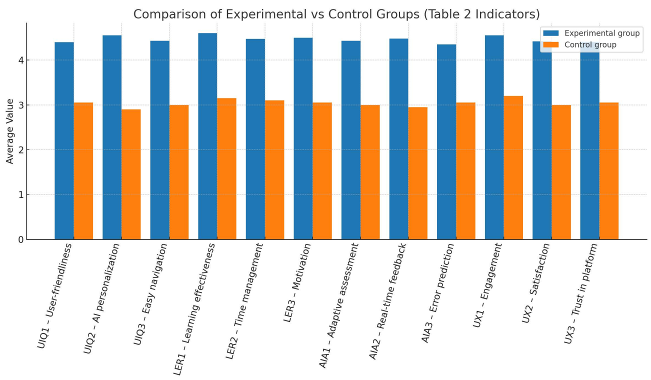

Fig. 5. Comparative bar chart of experimental vs. control group results on learning experience indicators.

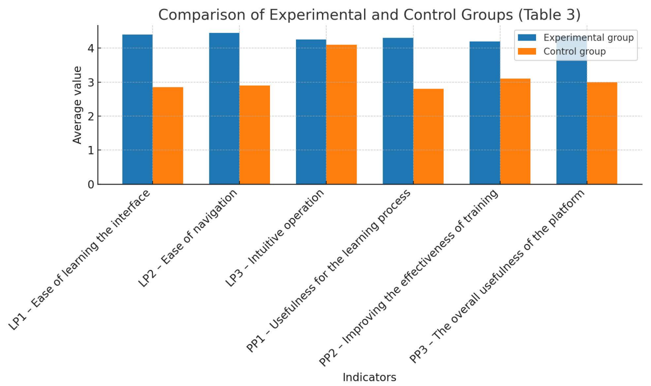

Fig. 6. Average values of learning experience indicators: Comparison between experimental and control groups.

V. Discussion

The proposed methodological framework "learning actions—interactive scenarios" answers research question 1 (RQ1) by identifying key learner behaviors that contribute to effective learning in a digital educational environment. The framework is based on the integration of situational learning theory and experiential learning theory, thereby emphasizing the idea that learning occurs through interaction in specific contexts and represents a cyclical process of transforming experience into knowledge.

By describing the mutual influence between learning behavior and contextual factors, the framework provides a holistic model for analyzing student behavior and expected learning outcomes, which helps to address research question 2 (RQ2).

In addition, the framework includes a digital technology component, expanding the scope of experiential learning in online education. The use of artificial intelligence for adaptation and personalization of learning enhances the impact of learning scenarios, making the platform more responsive to the individual needs of students. Thus, the methodological framework serves as an innovative tool for designing effective AI-based distance education systems.

The analysis confirms the effectiveness of the AI platform as a tool for improving the quality of distance education and facilitating interaction, thereby demonstrating the applicability of the conceptual framework "learning actions—interactive scenarios" to the design of digital educational solutions. In addition to statistical significance, effect size measures (Cohen's d) were calculated to clarify the magnitude of differences between the experimental and control groups. The obtained values ranged from medium to large, which confirms not only the statistical but also the practical significance of the proposed AI-based learning platform.

At the same time, the positive results of the control group in terms of basic navigation and accessibility indicate that both AI platforms and traditional solutions can be user-friendly. This highlights the need to further improve the personalization and adaptability of AI systems.

It should be noted that despite the support received for the theoretical positions, the study has limitations related to the sample size and duration of the experiment. To enhance the generalizability of the methodological framework, additional empirical studies with larger and more diverse samples in various online learning contexts are needed.

Moreover, there is a risk of systematic response bias, as students may have provided socially desirable answers or been affected by contextual factors during the survey. Another important limitation lies in the regional specificity of the sample, which restricts the generalizability of the findings to broader educational settings. Future research should address these threats to validity through mixed-method approaches, including interviews, classroom observations, and data triangulation, to ensure a more robust understanding of learner behavior and the effectiveness of AI-driven educational systems.

The proposed methodological framework provides a theoretical basis for stimulating the digital transformation of experiential learning in distance education systems, thereby answering research question 3 (RQ3). Digital technologies, especially artificial intelligence, enable the creation of immersive learning scenarios, offer diverse formats for information presentation, and support personalized and interactive learning models. This contributes to deeper knowledge assimilation and increases student satisfaction with the educational process.

The developed AI-based distance learning platform, as an example of practical implementation, demonstrates possible ways of digital transformation of education. It offers adaptive task-oriented learning plans, provides step-by-step navigation through educational content, and delivers in-depth interpretation of information tailored to each student's level.

However, the digital transformation in distance learning goes beyond technological solutions. It requires consideration of intercultural communication, especially in international or multicultural learning environments. When designing educational scenarios, it is important to account for the cultural adaptation of users, provide linguistic and cultural support, and create platforms for multidirectional interaction and understanding. This allows students to approach cultural differences with openness and respect, contributing to the formation of a digitally inclusive environment.

VI. Conclusion

This study contributes to the development of an understanding of experiential learning in distance education through artificial intelligence technologies by answering three key research questions.

First, the paper proposes a methodological framework "learning actions—interactive scenarios," based on the integration of situational learning theory and experiential learning theory. This framework offers a new perspective for analyzing digital educational interactions, especially in online learning environments where active student participation and the context of interaction play an important role.

Secondly, the study integrates the perspective of digital technologies, in particular artificial intelligence, which expands the theoretical and applied boundaries of experiential learning research. The distance learning platform with AI elements, examined in the empirical case study, confirmed the applicability and effectiveness of the proposed framework, demonstrating its potential for adaptive and personalized learning.

In the future, research should focus on conducting cross-cultural comparative analyses, developing strategies for personalized user support, and using modern data analysis methods (such as learning analytics and behavioral modeling) to build more accurate models of learner behavior in digital environments. These steps are important for optimizing digital educational environments and ensuring the sustainable development of AI-based distance learning systems. It should also be noted that the current study was limited by a relatively small sample size, which may affect the generalizability of the results. Future studies are encouraged to increase participant numbers to strengthen robustness. Moreover, informed consent was obtained from all participants, and data confidentiality was strictly maintained, thereby reinforcing the methodological integrity of the research.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Maxot Rakhmetov, Elmira Abdykerimova and Gadilbek Alzhanov conducted the literature search, analyzed the data and wrote the paper. Balaussa Orazbayeva and Bayan Kuanbayeva visualized the data and reviewed the manuscript. All authors have accepted the final version of the manuscript.

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