Journal of Theoretical and Applied Information Technology
30th April 2026. Vol.104. No.8

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

METHODOLOGICAL FOUNDATIONS OF AI-DRIVEN DISTANCE LEARNING PLATFORMS: EVIDENCE FROM LEARNING ANALYTICS AND STRUCTURAL EQUATION MODELING

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ABSTRACT

In the context of active digitalization of education, this study examines the effectiveness of distance learning in a digital educational environment based on the application of artificial intelligence principles in the design of educational platforms. The purpose of the research is to develop and empirically test a methodology for creating a distance learning platform that provides adaptive learning trajectories, personalization of educational content, and pedagogical decision-making based on data analysis.

As part of the research, a structural and functional model of an intelligent educational platform was developed and its pilot implementation in higher education was carried out. Empirical data was collected from students with different levels of digital competence and training. To assess the effectiveness of the proposed methodology, the methods of learning analytics, comparative analysis of educational results, as well as statistical modeling of educational data were used.

The results of the study show that adaptability and personalized feedback, implemented using artificial intelligence methods, are key factors in improving learning efficiency at the initial stages of using the platform, while student analytics and predicting learning outcomes become increasingly important at subsequent stages of learning. It has been established that continuous modeling of students' educational behavior and automatic correction of educational content contribute to increased engagement and sustained growth in academic performance.

In addition, differences in the effectiveness of learning between groups of students with different levels of initial digital readiness have been identified, which con-firms its moderating role in distance learning. The results obtained emphasize the need to integrate the principles of artificial intelligence into the methodological foundations of the development of distance learning platforms in order to increase personalization, optimize cognitive load and improve educational outcomes information

Keywords: *Artificial Intelligence; Distance Learning; Digital Educational Platforms; Adaptive Learning; Personalized Learning; Learning Analytics; Digital Readiness; Learning Effectiveness; Structural Equation Modeling; Higher Education.*

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1. INTRODUCTION

The effectiveness of distance learning is one of the key factors of academic success of students in the context of digital transformation of education [1]. Modern research shows that the quality of online learning is directly related not only to access to digital resources, but also to the ability to adapt the educational process to the individual characteristics of students, their cognitive characteristics and learning behavior [2,3]. In this context, distance learning is becoming particularly important as a tool for expanding educational opportunities, increasing the autonomy of students and developing self-education skills, critical thinking and digital competence [4-6]

At the same time, in a number of educational systems, including developing and transforming contexts, distance learning faces persistent problems such as low student engagement, insufficient personalization of educational content, limited feedback, and weak support for individual learning paths [7,8]. These limitations were particularly pronounced during the period of mass transition to online learning, revealing the structural deficits of traditional distance learning platforms focused primarily on content transfer rather than data-based learning process management [9-12]. In this regard, there is a need to develop methodologically sound distance learning models adapted to the digital educational environment and able to take into account the diversity of educational needs of students [13-15].

One of the promising ways to solve these problems is to apply the principles of artificial intelligence (AI) in the design and operation of distance learning platforms [16-18]. Modern AI approaches involve the use of machine learning methods, learning analytics, and intelligent recommendation systems to support adaptive learning, personalize content, and predict learning outcomes [19-22]. Unlike traditional digital platforms, AI-based systems view learning as a dynamic process in which learning decisions are made based on continuous analysis of learners' behavior and progress [23,24].

The methodological basis of AI-based distance learning is the representation of the educational process as a set of interrelated components, including educational content, learners, the digital environment and adaptation mechanisms [25-27]. Within the framework of this paradigm, the effectiveness of learning is determined not by the sum of individual elements of the platform, but by their coordinated functioning [28-30]. If at least one of the components — for example, a personalization mechanism or a feedback system — turns out to be insufficiently developed, this can significantly reduce educational outcomes [31-34]. This understanding highlights the need for a comprehensive methodological approach to the development of AI-based distance learning platforms [35].

Modern models of digital learning emphasize the importance of adaptive mechanisms, including consideration of the level of training of students, the pace of material assimilation, preferred forms of information presentation and motivational factors [36]. At the same time, research shows that adaptive navigation and personalized support play a key role in the early stages of using digital platforms, while at subsequent stages of learning, the importance of analytical tools, predicting learning difficulties and intelligent feedback increases [37]. However, existing platforms often implement these elements in fragments, without a single methodological basis, which limits their pedagogical effectiveness [38].

Of particular importance in the context of distance learning is the level of digital readiness of students, which includes digital literacy, self-regulation skills and the ability to independently manage learning activities [39]. Research indicates that there are significant differences in the results of online learning between groups of students with different levels of digital competence, which increases educational inequality and requires the development of adaptive solutions to compensate for these differences [40]. In this sense, artificial intelligence can act as a tool to reduce educational risks by individualizing learning and timely pedagogical intervention.

At the level of educational policy, the need for a transition from content-based distance learning models to data-oriented and student-centered platforms is increasingly emphasized. However, despite the active introduction of digital technologies, in most cases there is no clearly formulated methodology for the development of distance learning platforms based on the principles of artificial intelligence and pedagogically meaningful models of learning adaptation. This creates a gap between the technological potential of AI and its actual application in educational practice.

Based on the above, the present study pursues two main goals, focused on improving the practice and policy of distance education.:

(1) to develop a methodology for creating a distance learning platform based on the principles of artificial intelligence, providing adaptability,

personalization and support for data-based learning solutions;

(2) to empirically assess the impact of key AI components of the platform and the level of digital readiness of students on the effectiveness of distance learning in a digital educational environment.

Justification of research contribution.

This study contributes to the field of information technology in education by proposing a comprehensive methodological framework for integrating artificial intelligence into distance learning platforms. Unlike many existing studies that focus primarily on technical aspects, this research emphasizes the interaction between technological, pedagogical, and behavioral components, thereby addressing a significant gap in the current literature.

2. MATERIALS AND METHODS

2.1 Participants

The study involved 500 students in distance and mixed learning formats. The sample was formed on the basis of 18 educational institutions (public and private) using digital educational platforms, and covered students of various levels of training in a digital educational environment.

To analyze the dynamics of the effectiveness of distance learning, participants were divided into three clusters, depending on the stage of mastering digital educational technologies and educational content:

• the initial stage of using the platform (n = 165),
• intermediate stage of training (n = 170),
• Advanced stage of training (n = 165).

Data collection was carried out synchronously in public and private educational institutions in order to minimize differences related to external factors of digital infrastructure and temporary learning effects.

The assessment was conducted by specialists who had received preliminary methodological training as part of a research project, using unified data collection and processing procedures.columns.

2.2 Instruments

The effectiveness of distance learning, acting as a dependent variable of the study, was assessed on the basis of a set of indicators of educational effectiveness, student engagement and the sustainability of learning activity in the digital educational envi-ronment. These indicators were formed on the basis of data from the digital educa-tional platform, including the results of online assessment, behavioral analytics and logs of learning activity.

To form the learning adaptability factor (A), indicators of automatic adjustment of educational content were used, including the frequency of changes in the level of difficulty of tasks, the pace of completion of training modules, and the proportion of successfully completed adaptive tasks.

The learning personalization factor (P) included indicators of the compliance of educational recommendations with the individual profile of the student, the frequency of use of the recommendation subsystems of the platform, and the effectiveness of personalized feedback.

The Analytical Learning Support (LA) factor was represented by learning analytics indicators, including monitoring learning progress, predicting learning difficulties, and automated notifications of the risk of decreased learning activity.

Additional predictors of the effectiveness of distance learning included:

1. the level of digital competence of students;
2. indicators of self-regulation of learning activities in a digital environment;
3. The level of digital engagement calculated based on the frequency of login, activity in training modules and interaction with the elements of the platform.

The socio-demographic characteristics of the students were taken into account by means of a questionnaire. The index of socio-economic status was formed based on the level of education of parents, access to digital devices and the stability of the Internet connection at home.

2.3 Statistical analysis

Linear regression models using the SPSS (v.27.0.1.0) software package were used to determine the proportion of variability in the effectiveness of distance learning, ex-plained by artificial intelligence components and the platform design methodology.

Before constructing structural equation models (SEM), exploratory and confirma-tory factor analyses were performed, which allowed us to exclude indicators with fac-tor loads below 0.50 in accordance with the acceptance criteria proposed by Suresh-chandar and confirms the correspondence of empirical factors to the theoretical re-search model [41].

The final SEM models demonstrated satisfactory agreement between the model and empirical data in accordance with the recommendations of Cheung et al. [42,43]. Factor analysis and SEM were performed using the JASP (v.0.18.3) software package refer to table 1.

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Table 1: Kolb's Model In The Context Of AI Distance Learning

The learning stage	Selection	χ² (df), p	CFI	TLI	RMSEA	SRMR
The initial stage	n = 165	χ²(78) = 146.32, p < 0.001	0.96	0.95	0.06	0.06
The intermediate stage	n = 170	χ²(102) = 198.47, p < 0.001	0.95	0.94	0.06	0.07
Advanced stage	n = 165	χ²(128) = 214.89, p < 0.001	0.96	0.95	0.05	0.06

Despite the robustness of the applied statistical methods, several threats to the validity of the study should be considered. First, the use of self-reported and platform-generated data may introduce measurement bias. Second, the selection of indicators for adaptability, personalization, and analytics, although theoretically grounded, may not fully capture the complexity of learning processes. Additionally, the sample, while diverse, is limited to specific educational contexts, which may affect the generalizability of the results. Future studies should consider broader and more heterogeneous samples, as well as longitudinal designs to improve reliability.

3. RESEARCH RESULTS

Objective 1: to analyze the functioning of the principles of artificial intelligence and the contribution of the key components of the platform to the effectiveness of distance learning.

Linear regression models were constructed to assess the proportion of variability in the effectiveness of distance learning, explained by the components of an intelligent educational platform. The integral effectiveness of distance learning was considered as a dependent variable, and the key AI components of the platform were used as predictors: adaptability of learning, personalization of content, and analytical support for learning.

Adjusted values of the coefficient of determination (R2) showed that the combination of platform components explains 49% of the variability in learning effectiveness at the initial stage of using the platform (F(9.155) = 18.42, p < 0.001), 31% at the intermediate stage (F(9.160) = 8.73, p < 0.001) and 27% at the at the advanced stage of training (F(9.155) = 6.84, p < 0.001). The results obtained indicate a high explanatory ability of the platform development methodology, especially in the early stages of its use.

The constructed models of structural equations (SEM) for the three stages of learning (Figures 1-3) showed that learning adaptivity has the greatest impact on the effectiveness of distance learning at the initial stage (β = 0.71, p < 0.001), while its contribution decreases at the intermediate (β = 0.38, p < 0.001) and advanced stages (β = 0.22, p < 0.001.

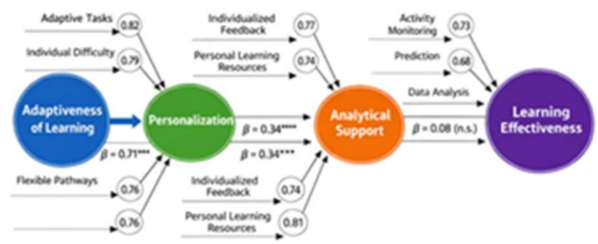

Figure 1: Structural Model Of Distance Education Effectiveness: Initial Stage.

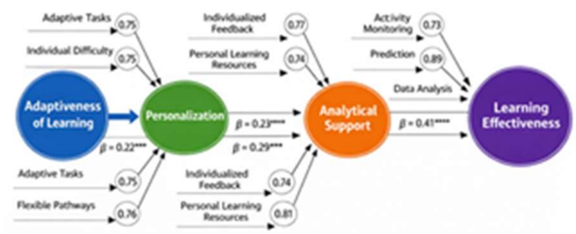

Figure 2: Structural Model Of Distance Education Effectiveness: Advanced Stage

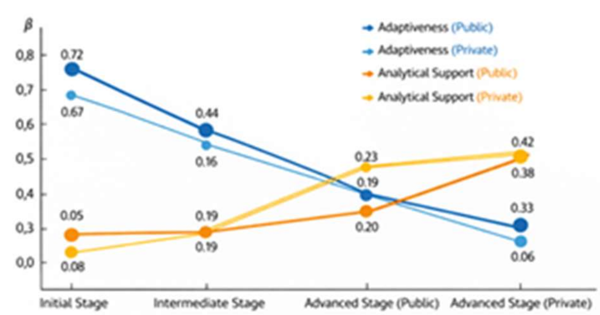

Figure 3: Comparison Of The Contribution Of Distance Education Components Over Time: Public Vs. Private

In contrast, the contribution of analytical support for learning, implemented using learning analytics and predictive models, was statistically insignificant at the initial stage, but increased as data on students accumulated, reaching β = 0.29 (p < 0.001) at the intermediate and β = 0.41 (p < 0.001) at the advanced

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

stages of learning.

The learning personalization factor made a stable and significant contribution to the effectiveness of distance learning at all stages, demonstrating moderate but stable regression coefficients (β = 0.34; β = 0.31; β = 0.29; p < 0.001 for all stages).

The analysis of the contribution of behavioral and cognitive predictors showed that the digital competence of students has a significant impact on the use of adaptive and analytical mechanisms of the platform (β = 0.47, p < 0.001), especially at the initial stages of working with the system. At the same time, learning self-regulation indicators reinforced the contribution of analytical support at an advanced stage, confirming the role of executive functions in distance learning.

Objective 2: to analyze the impact of the socio-economic status and type of educational organization on the functioning of the platform components.

The impact of students' socio-economic status (SES) on the effectiveness of distance learning remained significant at all stages of using the platform, but showed a downward trend. The cumulative contribution of SES to learning effectiveness was β = 0.44 (p < 0.001) at the initial stage, β = 0.28 (p < 0.001) at the intermediate stage, and β = 0.19 (p < 0.001) at the advanced stage.

Regression analysis with the separation of the sample by type of educational organization (public and private) showed that the components of the AI platform explain a greater proportion of the variability in learning effectiveness in public educational organizations than in private ones. So, at the initial stage, R2 was 53% in public organizations ($F(9.82) = 10.94$, $p < 0.001$) versus 44% in private organizations ($F(9.73) = 6.41$, $p < 0.001$). A similar trend was observed at the intermediate (34% vs. 26%) and advanced stages of education (29% vs. 18%).

For a more detailed analysis of the differences in the functioning of the platform components, separate SEM models were built for students of public and private educational organizations at each stage of training (Figure 4). In these models, SES indicators were not included due to the limited intra-group variability of socio-economic indicators

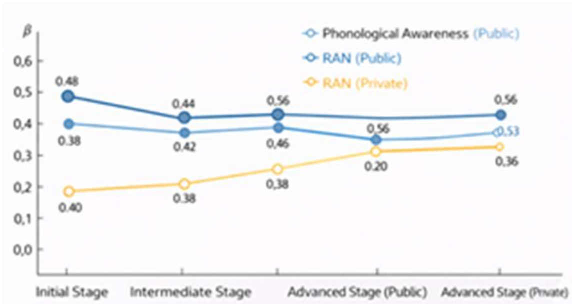

Figure 4: Comparison Of The Influence Of Predictors In Decoding Over Time: Public Vs. Private

A comparative analysis of regression coefficients (Figure 5) showed that in private educational institutions, the transition from the dominance of adaptive mechanisms to analytical support for learning occurs at an earlier stage, whereas in public organizations, adaptivity retains a significant influence until the advanced stage of learning. At the final stage, the contribution of adaptability in private organizations became statistically insignificant, while in public organizations it remained at the level of β = 0.23, with the dominant influence of analytical support (β = 0.42).

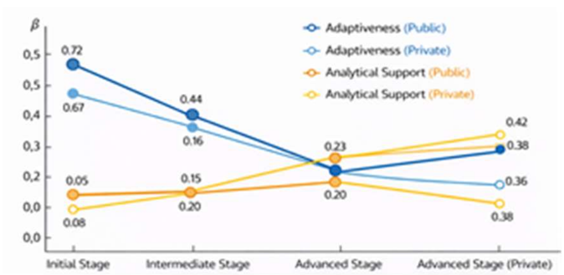

Figure 5: Comparison Of The Contribution Of Adaptiveness And Analytical Mechanisms Over Time: Public Vs. Private Education

A similar differentiation was observed in the dynamics of the use of personalization and analytics mechanisms. In public educational organizations, personalization maintained a steady contribution at all stages, while in private organizations its importance gradually decreased as automation of analytical tools increased. By the final stage of training, the contribution of personalization and analytical support in both systems was converging, which indicates the convergence of learning models with sufficient duration of use of the platform (Figure 6).

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

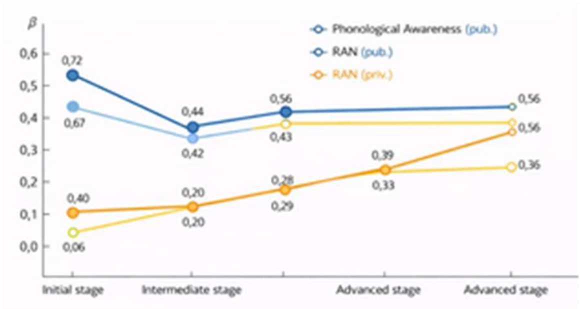

Figure 6: Comparison Of Adaptive And Analytic Mechanism Contributions: Public Vs. Private

4. DISCUSSION

The purpose of this study was to analyze the functioning of the principles of artificial intelligence in the structure of distance learning, to determine the contribution of key components of the intellectual educational platform to the effectiveness of learning, as well as to study the impact of socio-economic status and type of educational organization on the operation of these mechanisms.

In general, the results obtained confirm the theoretical positions of modern models of intellectual and adaptive learning. As expected, in the early stages of using the platform, the adaptability of the educational process has the greatest impact on the effectiveness of distance learning, ensuring an individual selection of the complexity of tasks, the pace of learning and the routes of mastering the content. As learning data accumulates and students' digital maturity increases, the role of analytical support and predictive mechanisms increases, while the contribution of adaptive mechanisms gradually decreases.

The specificity of the digital educational context under study lies in the fact that the influence of adaptive mechanisms remains statistically significant even at an advanced stage of education, especially in public educational institutions. This indicates that the automation of learning processes and the development of self-regulation among students is slower than expected in theoretical models focused on highly developed digital environments. In such conditions, adaptivity continues to perform a compensatory function, supporting students with insufficiently developed skills in self-management of learning.

A different dynamic is observed in private educational institutions: the transition from the dominance of adaptive mechanisms to analytical support occurs at earlier stages. This may be due to a higher level of digital readiness of students, stable access to technology, and more intensive use of the platform's data to make learning decisions. Thus, the differences in the functioning of the platform components reflect not so much the technological features of the system as the contextual differences in the educational environment.

The sustained contribution of personalizing learning at all stages of using the platform deserves special attention. Regardless of the level of education and the type of educational organization, personalized recommendations, individual resources and feedback demonstrate a stable impact on the effectiveness of distance learning. This is consistent with the provisions of cognitive load theory and student-centered learning models, according to which matching the content and form of information presentation with the individual characteristics of students is a critical factor for successful learning in a digital environment.

The results also indicate that the socio-economic status of students continues to influence the effectiveness of distance learning, although its contribution gradually decreases as students' progress through the educational stages. This suggests that the intelligent mechanisms of the platform partially compensate for the initial differences related to access to resources and the level of digital support outside the educational organization. However, these differences are not completely eliminated, which underscores the need for comprehensive educational solutions combining technological and socio-pedagogical measures.

A comparison of the results obtained with studies in other digital educational contexts shows that the explanatory ability of intelligent distance learning models varies depending on the level of digital development of the environment and the readiness of students. A higher proportion of the explained variability in public educational institutions may indicate that in conditions of more pronounced restrictions, the influence of structured AI mechanisms is more pronounced. In a more favorable environment, learning effectiveness is determined by a wider range of factors beyond the model.

Despite the fact that this study is focused on analyzing the effectiveness of distance learning rather than diagnosing individual learning difficulties, it cannot be ruled out that some of the students identified patterns reflect persistent problems of digital adaptation and self-regulation. This indicates the prospects for further research aimed at integrating artificial intelligence models with psychological and pedagogical theories that take into account the cognitive, behavioral and motivational characteristics of students.

ISSN: 1992-8645 www.jatit.org E-ISSN: 1817-3195

In general, the results of the study emphasize the need to develop and implement methodologically sound distance learning platforms based on the principles of artificial intelligence, which not only automate educational processes, but also flexibly adapt to the context, supporting students at different stages of digital learning and reducing educational risks.

Critical evaluation and comparison with previous studies.

This study provides important insights into the effectiveness of AI-driven distance learning platforms; however, several limitations and critical aspects should be acknowledged. Compared to recent studies the present research focuses more on the structural integration of AI components rather than on specific algorithmic implementations. While previous works emphasize technological optimization, this study contributes by highlighting the methodological and pedagogical alignment of AI tools within the learning process.

At the same time, unlike some recent empirical studies, the explanatory power of the model decreases at advanced stages of learning, which may indicate the presence of additional external variables not captured in the current model. This suggests that learning effectiveness in mature stages is influenced by more complex cognitive, motivational, and contextual factors.

Furthermore, the study does not fully account for long-term learning outcomes or cross-cultural differences, which are increasingly addressed in contemporary research. These aspects remain open for further investigation

5. CONCLUSION

The present study was aimed at analyzing the effectiveness of distance learning in a digital educational environment from the perspective of applying the principles of artificial intelligence and developing a methodology for an intelligent educational platform. The results obtained confirm that the integration of adaptive, personalized and analytical mechanisms based on artificial intelligence significantly increases the effectiveness of distance learning, especially in the early stages of using digital platforms.

It has been established that adaptivity of learning plays a leading role at the initial stage, ensuring that the complexity of learning tasks, the pace of material development and learning routes are consistent with the individual characteristics of students. As data accumulates and self-regulation skills develop, the contribution of analytical support and predictive mechanisms increases, reflecting the transition from direct learning-based adaptation to data-based learning process management.

Personalization of learning has demonstrated a sustained impact on the effectiveness of distance learning at all stages, confirming its key role in student-centered models of digital education. This indicates the need to systematically integrate personalized recommendations and individual feedback into the architecture of distance learning platforms.

The results of the study also revealed the continuing influence of the socio-economic status and type of educational organization on the effectiveness of distance learning. At the same time, the observed decrease in the contribution of these factors as students' progress through the learning stages suggests that the intelligent mechanisms of the platform are able to partially compensate for the initial differences related to the level of digital readiness and access to educational resources.

A comparative analysis of the functioning of platform components in public and private educational organizations has shown that in conditions of more pronounced restrictions, the role of structured and adaptive AI mechanisms increases, whereas in more favorable digital conditions, the effectiveness of learning is determined by a wider range of factors. This highlights the contextual sensitivity of intelligent educational solutions and the need to adapt them to the specifics of the educational environment.

In general, the results of the study confirm the expediency of developing methodologically sound distance learning platforms based on the principles of artificial intelligence. Such platforms are able not only to automate educational processes, but also to ensure a steady increase in learning efficiency by adapting to the individual and contextual characteristics of students, which makes them a promising tool for the development of digital education.

Extended conclusion with strengths, weaknesses, and future research.

In addition to the achieved results, the authors consider this study as an important step toward the development of methodologically grounded ai-driven educational systems. One of the key strengths of the research lies in the integration of structural equation modeling with learning analytics, which allows for a comprehensive assessment of the effectiveness of distance learning.

However, the study also has several limitations. In particular, the model does not fully account for external socio-cultural factors, long-term learning outcomes, and psychological variables influencing student behavior. These limitations highlight the need for further refinement of the proposed methodology.

From the authors' perspective, the presented work demonstrates strong potential for practical application, but requires further validation in diverse educational contexts and with more advanced ai techniques.

Future research should focus on:

expanding the range of predictive variables, including motivational and emotional factors;

conducting longitudinal studies to assess long-term learning outcomes;

integrating more advanced machine learning models into educational platforms;

exploring cross-cultural differences in digital learning environments.

These directions will help to overcome the current limitations and enhance the applicability of AI-driven distance learning systems.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

FUNDING

This work was financially supported by the Science Committee of the Ministry of Science and Higher Education of the Republic of Kazakhstan (grant AP25796073, 2025 W2027).

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