Online-Journals.org

iJIM International Journal of Interactive Mobile Technologies

iJIM | eISSN: 1865-7923 | Vol. 20 No. 21 (2026) | OPEN ACCESS

https://doi.org/10.3991/ijim.v20i21.62672

PAPER

An Adaptive Web Platform for Personalized Learning Using Digital Competence Modeling and Fuzzy Inference

Zhanat Seitakhmetova[1], Zhalgasbek Iztayev[2] (✉), Kamalbek Berkimbayev[3], Egemberdy Tenizbaev[4], Symbat Nurgaliyeva[5], Zhanbota Bakytova[6]

[1]Sarsen Amanzholov East Kazakhstan University, Ust-Kamenogorsk, Kazakhstan

[2]M. Auezov South Kazakhstan University, Shymkent, Kazakhstan

[3]Khoja Akhmet Yassawi International Kazakh-Turkish University, Turkestan, Kazakhstan

[4]Central Asian Innovation University, Shymkent, Kazakhstan

[5]Astana IT University, Astana, Kazakhstan

[6]Nazarbayev Intellectual Schools, Astana, Kazakhstan

zhalgasbek.iztaev@auezov.edu.kz

ABSTRACT

The development of digital educational ecosystems and personalized learning technologies has created a growing demand for intelligent adaptive educational platforms. This paper presents an adaptive web-based educational platform based on digital competence modeling, learner profiling, and a recommendation mechanism using the Mamdani fuzzy inference approach. Digital competence weights were determined using the Analytic Hierarchy Process (AHP) based on expert evaluation. The recommendation model employed three input variables: subject knowledge level, English language proficiency, and the integrated Digital Competence Score. The knowledge base comprised 27 production rules, and recommendations were generated using Mamdani fuzzy inference with centroid defuzzification. The platform was implemented using ASP.NET, Microsoft SQL Server, and MATLAB Fuzzy Logic Toolbox and was evaluated in a quasi-experimental study involving 129 upper secondary school learners from six intact classes across two schools. The principal analysis of the original final-assessment scores showed no statistically significant difference between the groups; however, the secondary exploratory analysis based on the predefined ≥70% final-assessment threshold showed a significantly higher proportion of learners reaching the threshold in the experimental group, and this individual-level threshold analysis was not adjusted for allocation through intact classes. Experimental-group questionnaire responses indicated generally positive perceptions of several aspects of platform use and were analyzed descriptively. These exploratory findings indicate the potential of an interpretable rule-based recommendation model to support personalized learning, while class-, school-, teacher-, and intervention-condition effects cannot be securely separated in the present study.

KEYWORDS

adaptive web-based educational platform, personalized learning, learner profiling, digital competence modeling, analytic hierarchy process (AHP), Mamdani fuzzy inference, educational recommender systems

Seitakhmetova, Z., Iztayev, Z., Berkimbayev, K., Tenizbaev, E., Nurgaliyeva, S., Bakytova, Z. (2026). An Adaptive Web Platform for Personalized Learning Using Digital Competence Modeling and Fuzzy Inference. *International Journal of Interactive Mobile Technologies (iJIM)*, 20(21), pp. 17–39. https://doi.org/10.3991/ijim.v20i21.62672

Article submitted 2026-06-18. Revision uploaded 2026-09-15. Final acceptance 2026-09-23.

© 2026 by the authors of this article. Published under CC-BY.

1 INTRODUCTION

The digital transformation of education has been accompanied by the widespread adoption of web-based and mobile-accessible educational technologies and intelligent educational platforms designed to support personalized learning. Contemporary mobile learning environments provide continuous access to educational resources regardless of time and location, increase the flexibility of the learning process, and create opportunities for developing personalized learning pathways [1]–[4]. Under these conditions, intelligent educational systems capable of considering individual learner characteristics and adapting educational content to learners' needs and proficiency levels have become increasingly important. Digital competence can also be incorporated into learner profiles used for personalized educational recommendations. Recent research has addressed adaptive learning, learner modelling, educational recommender systems, and digital competence from different perspectives [1]–[6]. Fuzzy logic provides an established rule-based approach for representing decision processes under uncertainty [7], [8]. In this study, these established approaches are combined within a single learner-profile-based recommendation architecture. Therefore, the aim of this study is to develop and evaluate an adaptive web-based system that integrates learner profiling, digital competence assessment, AHP-based weighting, and Mamdani fuzzy inference to generate educational package recommendations.

The platform was implemented as a web-based system accessible through desktop and mobile web browsers. Mobile interaction was not evaluated as a separate component of the intervention; device types, the proportion of mobile sessions, and mobile-access frequency were not recorded. Accordingly, mobile access is treated in this study as an implementation feature rather than as an empirically evaluated component of the platform.

1.1 Literature review

Digital educational platforms are important tools for improving the accessibility and flexibility of learning and can provide access to educational resources from different types of devices. Seitakhmetova et al. examined university students' views on mobile technology and Moodle applications in personalized learning and reported generally positive student perceptions [9]. Yaghmour et al. systematically reviewed AI-driven adaptive learning systems in mobile education, focusing on personalization strategies, effectiveness, and user interaction [10]. Li proposed a mobile-oriented intelligent education framework based on a three-layer architecture and multimodal data-driven personalized adaptation [11]. A systematic review by Hariyanto et al. showed that adaptive educational systems personalize learning by analyzing learner characteristics and automatically adapting educational content [3]. Strielkowski et al. examined the role of AI-driven adaptive learning in personalized education and educational transformation [4]. Long et al. systematically reviewed the role of artificial intelligence in higher education, with particular attention to student engagement and teaching methods [5].

More broadly, Alamri et al. reviewed learning technology models supporting personalization in blended higher education and highlighted the limited availability of data-driven independent evidence concerning their effectiveness and impact on student learning [2]. Tan et al. reviewed AI-enabled adaptive learning platforms, including their pedagogical foundations, learner-data-driven adaptation,

core algorithms, evaluation approaches, and recommender-system functions [6]. These reviews indicate that personalization involves not only the delivery of digital content but also learner modeling, adaptation mechanisms, and the evaluation of resulting learning experiences and outcomes.

One of the key factors influencing successful learning in a digital educational environment is learners' digital competencies. The DigComp 2.2 framework defines digital competence as a set of five interconnected competence areas and provides a universal approach to their assessment [1]. Similar principles are reflected in the DigCompEdu framework [12], which focuses on the integration of digital technologies into educational practice.

Related studies have also examined student-centered digital learning, emerging educational technologies, and adaptive learning in different educational contexts. Researchers report that digital educational technologies and learner-centered approaches contribute to the development of digital literacy and independent learning skills [13]. Mendekenova et al. compared teachers' perceptions of AI, VR/AR, and gamification in foreign-language education [14]. Zulpykhar et al. developed an adaptive educational platform for mathematics education and reported statistically significant improvements in academic achievement, learning motivation, and learner engagement through the use of personalized learning pathways [15]. These studies illustrate different uses of digital technologies, learner-oriented approaches, and adaptive learning in educational settings rather than a single uniform model of personalized learning.

Fuzzy logic provides an established approach for representing rule-based decision processes under conditions of uncertainty. The foundations of this approach were established by Mamdani, whose work introduced fuzzy algorithms for rule-based control [7]. Recent studies have applied fuzzy systems to classification and decision-support tasks. For example, Ramanath and Hossen proposed an incremental-learning-based parallel fuzzy reasoning system for classification under uncertain data conditions [8]. In educational recommendation, Shareef et al. [16] combined a fuzzy expert system with self-attention to generate explainable course recommendations. Shen [17] applied a Takagi–Sugeno fuzzy model within a platform for recommending educational resources. For the present study, the relevance of fuzzy inference lies in its capacity to express the implemented decision logic through explicit linguistic rules rather than in treating fuzzy inference itself as a methodological novelty.

To position the present study more precisely, comparison is made with identifiable works in the reviewed literature that address aspects directly related to the proposed platform. Seitakhmetova et al. [9] addressed mobile technology and Moodle in personalized learning; Yaghmour et al. [10] reviewed AI-driven adaptive learning systems in mobile education; Li [11] proposed a mobile-oriented framework incorporating personalized adaptation; and Zulpykhar et al. [15] developed and evaluated a personalized adaptive learning platform in mathematics education. These studies were selected because they address the strands most directly related to the present work: personalized and adaptive learning, learner-oriented digital technologies, mobile interaction, and adaptive educational platforms. Their objectives, methods, and evaluation settings differ; therefore, they are not treated as a homogeneous category of "existing platforms."

Against this background, the contribution of the present study does not lie in learner profiling, AHP, Mamdani fuzzy inference, or browser-based access considered individually. Rather, the study integrates subject knowledge, English language proficiency, and digital competence within a learner profile, uses AHP to weight the

components of the Digital Competence Score, and combines these inputs through a 27-rule Mamdani fuzzy inference mechanism to recommend an educational package within a single adaptive web-based platform. The recommendation mechanism underwent functional verification for conformity with the specified fuzzy rule base but was not independently validated. The subsequent quasi-experimental evaluation concerns the implemented educational intervention and is therefore distinguished from validation of the recommendation mechanism itself. A transferable design aspect of the proposed approach is the use of an explicit rule-based architecture for combining multiple learner characteristics into interpretable educational package recommendations.

2 MATERIALS AND METHODS

2.1 Research design

The research methodology consisted of four sequential stages: development of a digital competence model for learners based on a review of the scientific literature and expert evaluation; determination of digital competence component weights using the Analytic Hierarchy Process (AHP); development of a personalized recommendation mechanism based on Mamdani fuzzy inference; and implementation and experimental evaluation of an adaptive web-based platform.

Learning outcomes were assessed using a final assessment consisting of practical tasks designed to evaluate mastery of the competencies specified in the course. Scores ranged from 0 to 100%, with a predefined threshold of ≥70% indicating successful attainment. The threshold was established before the analysis on the basis of expert evaluation by teachers. The same assessment procedure, scoring scale, and achievement criterion were applied to both the experimental and control groups (CG). The final assessment was administered at the end of the 20-week experimental period and was graded using anonymized learner codes; therefore, assessors were blinded to group allocation during grading. No final assessment scores were missing or excluded.

2.2 Learners' digital competence model

To construct the learner's digital profile, a digital competence model was developed based on the international DigComp 2.2 framework [1] and recent studies on adaptive learning [3]. The preliminary model structure, developed through a review of the scientific literature and international digital competence frameworks, was subsequently refined through expert evaluation.

The evaluation of the digital competence model involved 54 participants. The domain expert group comprised four senior managers of the Autonomous Educational Organization Nazarbayev Intellectual Schools (AEO NIS), six school administrators, and twenty teachers holding the qualification categories "teacher-expert" and "teacher-researcher." The stakeholder group comprised twelve parents and twelve Grade 11–12 learners of Nazarbayev Intellectual Schools who were at least 18 years old at the time of the study. The domain experts evaluated the importance of digital competence components from the perspectives of educational management and teaching practice, whereas parents evaluated them from the perspective of

supporting learners' educational activities, and learners acted as direct users of the digital educational environment.

The evaluation was conducted using a structured questionnaire that included digital competence groups and their components. Participants performed pairwise comparisons of competence components within each group using Saaty's nine-point scale [18]. Individual judgments were aggregated using the geometric mean and subsequently used to determine component weights by means of the AHP. Consistency was assessed for the aggregated matrices; individual participant matrices were not separately assessed for consistency. No additional group-level weighting was applied. Differences between participant groups were not analyzed because this was not an objective of the present stage of the study.

As a result, the final digital competence model, comprising five interrelated competence groups and 21 components, was developed (refer to Table 1).

Table 1. Final structure of the digital competence model

Competence Group	Main Components
Information literacy	Searching, filtering, and retrieving data and digital content; evaluating information; managing data and digital content; collecting, organizing, storing, and protecting information; data processing and analysis
Digital communication and collaboration	Interaction through digital technologies; collaboration using digital technologies; sharing digital content; digital identity management
Digital content creation	Creating and developing digital content; programming; application development; integrating and modifying digital content
Safety	Protecting health and well-being; protecting personal data and privacy; information security management
Problem solving	Identifying digital competence gaps and self-development; solving technical problems; creative use of digital technologies; problem management; identifying needs and selecting technological solutions

The digital competence model was used to construct the learner profile and provided the basis for deriving the digital competence indicator subsequently used in the recommendation subsystem. Digital competence was assessed using an author-developed instrument covering the 21 components retained in the final model. Each component included 10 closed-response theoretical and practically oriented items, scored dichotomously (1 = correct; 0 = incorrect). The resulting component score (S_i) ranged from 0 to 10 and was normalized to [0, 1] as ($C_i = S_i/10$). The assessment was administered electronically under supervised conditions, with students completing the test individually on computers. All items required a response; therefore, there were no missing responses. The component mapping, scoring and normalization procedures, and an anonymized worked example based on an actual learner response sheet are provided in Supplementary File S1. The complete 210-item instrument in the original Kazakh-language version is provided separately in Supplementary File S2.

Before the main study, the instrument was pilot-administered to three students to check item comprehensibility, approximate difficulty, content accessibility, and completion time. This pilot was used for practical refinement and did not constitute formal psychometric validation; validity and reliability coefficients were not calculated.

2.3 Determination of competence weights using the AHP

To determine the relative importance of individual digital competencies, the AHP proposed by T. Saaty was applied [18]. A hierarchical structure comprising the evaluation goal, digital competence groups, and their components was constructed. Pairwise comparisons were performed among components within each competence group using Saaty's fundamental nine-point scale.

No separate higher-level pairwise comparison among the five competence groups was conducted.

After aggregation of individual judgments using the geometric mean, row geometric means for the aggregated pairwise-comparison matrix were calculated as:

$$GM_i = \left(\prod_{j=1}^{n} a_{ij} \right)^{\frac{1}{n}}$$

where GM_i is the geometric mean for the i-th component; a_{ij} is the pairwise comparison value between the i-th and j-th components; and n is the number of components in the pairwise comparison matrix.

The obtained values were normalized to determine the local priority weights (Normalized Priority Vector, NPV):

$$NPV_i = \frac{GM_i}{\sum_{k=1}^{n} GM_k}$$

where NPV_i is the normalized priority weight of the i-th component; GM_i is the geometric mean of the corresponding component; and $\sum_{k=1}^{n} GM_k$ is the sum of the geometric means of all components within the corresponding competence group.

The consistency of the expert judgments was evaluated using the Consistency Index (CI) and the Consistency Ratio (CR):

$$CI = \frac{\lambda_{max} - n}{n - 1}, \; CR = \frac{CI}{RI},$$

where λ_{max} is the principal eigenvalue of the pairwise comparison matrix; n is the matrix size; and RI is Saaty's Random Index.

Matrices were considered consistent when $CR < 0.10$. All aggregated pairwise comparison matrices satisfied this criterion. Individual participant matrices were not evaluated separately using the CR. Consequently, the extent to which potentially inconsistent individual judgments may have influenced the aggregated priorities is unknown.

Components were selected using the criterion NPV ≥ 0.10. Components satisfying this criterion were retained in the final model, whereas components with lower relative importance were excluded to reduce model redundancy. A summary of the AHP results is presented in Table 2, while the local priority weights, component rankings, matrix consistency indicators, and the final normalized component weights used to calculate the Digital Competence Score are provided in Supplementary File S3. The original individual and aggregated pairwise-comparison matrices were not retained in a form permitting independent reconstruction. Therefore, the reported local priority weights and consistency statistics cannot be independently recalculated from the original pairwise judgments. However, the subsequent calculation of the final

normalized component weights from the reported local NPV values can be verified using the data provided in Supplementary File S3.

Table 2. Summary of the AHP results for the digital competence model

Competence Group	Initial Components	Selected	Excluded	Matrix Size	λ_{max}	*CI*	*RI*	*CR*
Information literacy	7	5	2	7 × 7	7.565	0.094	1.32	0.071
Digital communication and collaboration	5	4	1	5 × 5	5.429	0.107	1.12	0.096
Digital content creation	5	4	1	5 × 5	5.059	0.015	1.12	0.013
Safety	5	3	2	5 × 5	5.101	0.025	1.12	0.023
Problem solving	6	5	1	6 × 6	6.070	0.014	1.24	0.011
Total	28	21	7	–	–	–	–	–

As shown in Table 2, all aggregated pairwise comparison matrices demonstrated an acceptable level of consistency ($CR < 0.10$). Consequently, 21 of the initial 28 components were retained in the final model.

After selecting the 21 components with NPV ≥ 0.10, the retained local priority weights from all competence groups were pooled without applying additional group-level weights and re-normalized with respect to the total sum of the retained local NPV values. Because no separate higher-level comparison of the five competence groups was conducted, no empirically derived group-level AHP weights were available. The final normalized weight of each retained component (W_i) was calculated as the ratio of its local NPV value to the sum of the retained local NPV values. This procedure ensured that $\Sigma W_i = 1$ and enabled the resulting indicator to be used as a continuous input variable of the fuzzy inference model. This operational normalization produced a single set of component weights and should not be interpreted as a complete hierarchical AHP procedure with independently estimated group-level priorities.

The integrated Digital Competence Score was calculated as the weighted sum of the normalized values of the 21 retained components:

$$DC = \Sigma_{i=1}^{21} W_i C_i,$$

where DC is the integrated digital competence level of the learner; W_i is the final normalized weight of the i-th component; C_i is the normalized value of the corresponding component; and 21 is the number of components retained in the final model.

Because the final normalized weights were re-normalized so that $\Sigma W_i = 1$, the Digital Competence Score also ranges from 0 to 1. The resulting score served as one of the three input variables of the recommendation subsystem together with subject knowledge level and English language proficiency.

A formal sensitivity analysis using alternative NPV threshold values was not performed; therefore, the stability of the selected component set with respect to changes in the threshold was not evaluated.

2.4 Adaptive recommendation model based on fuzzy inference

The integrated Digital Competence Score calculated in the previous stage, together with subject knowledge level and English language proficiency, was used in a Mamdani Fuzzy Inference System (FIS) to generate personalized educational recommendations. The model comprised three input variables and one output variable: X_1 – subject knowledge level; X_2 – English language proficiency; X_3 – Digital Competence Score; and Y – a fuzzy output variable representing the recommended educational package. After defuzzification, a crisp output value Y* was obtained.

The four educational packages represented progressively more advanced course levels. Package assignment was not determined by a single difficulty indicator but by the 27-rule fuzzy knowledge base combining three learner characteristics: subject knowledge, English language proficiency, and digital competence. Package 1 represented the most supportive level, whereas Package 4 represented the most advanced level, with Packages 2 and 3 providing intermediate levels according to different combinations of the three input variables. The complete mapping of the 27 input combinations to the four educational packages is provided in Supplementary File S4.

The architecture of the decision-making mechanism, including fuzzification, the rule base, fuzzy inference, and defuzzification, is presented in Figure 1.

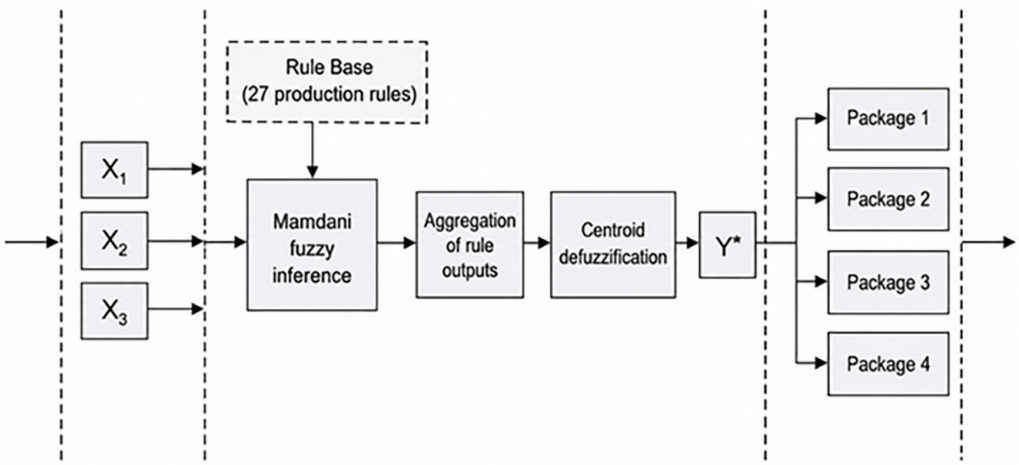


Fig. 1. Architecture of the fuzzy-inference-based decision-making mechanism

All variables were represented within the normalized interval [0, 1]. The initial subject knowledge score S_1 was measured as the percentage of correctly completed tasks (0–100%), whereas the English language proficiency score S_2 was assessed on a seven-point scale (0–7). Normalization was performed as follows:

$$X_1 = \frac{S_1}{100}, \; X_2 = \frac{S_2}{7}.$$

The variable X_3 represented the integrated Digital Competence Score calculated in the previous stage using the AHP and was already normalized to the interval [0,1]; therefore, no additional transformation was required.

Linguistic variables and membership functions. Three linguistic terms were defined for each input variable: X_1 – Low, Threshold, and High; X_2 – Basic, Intermediate, and Advanced; X_3 – Intermediate, Confident, and Advanced. The output variable Y consisted of four linguistic terms: Package 1, Package 2, Package 3, and Package 4.

All linguistic terms were represented using trapezoidal membership functions (trapmf) defined by four parameters (a, b, c, d):

$$\mu(x;a,b,c,d)=\left\{0,x\le a;\frac{x-a}{b-a},a<x<b;1,b\le x\le c;\frac{d-x}{d-c},c<x<d;0,x\ge d\right\}$$

where a and d define the support boundaries of the membership function, whereas b and c define the interval of full membership. When $a = b$ or $c = d$, the function formed a left-shoulder or right-shoulder membership function, respectively. The numerical parameters are presented in Table 3. The model was implemented using the MATLAB Fuzzy Logic Toolbox.

Table 3. Parameters of the input and output variables of the fuzzy inference model

V.	Interpretation	Universe of Discourse	Linguistic Terms	Membership Function	Parameters (a, b, c, d)
X_1	Subject knowledge level	[0, 1]	Low	trapmf	[0, 0, 0.40, 0.60]
			Threshold	trapmf	[0.40, 0.60, 0.80, 0.90]
			High	trapmf	[0.80, 0.90, 1, 1]
X_2	English language proficiency	[0, 1]	Basic	trapmf	[0, 0, 0.30, 0.35]
			Intermediate	trapmf	[0.30, 0.35, 0.65, 0.70]
			Advanced	trapmf	[0.65, 0.70, 1, 1]
X_3	Digital Competence Score	[0, 1]	Intermediate	trapmf	[0, 0, 0.55, 0.65]
			Confident	trapmf	[0.55, 0.65, 0.70, 0.80]
			Advanced	trapmf	[0.70, 0.80, 1, 1]
Y	Recommended educational package	[0, 1]	Package 1	trapmf	[0, 0, 0.03, 0.39]
			Package 2	trapmf	[0.30, 0.39, 0.45, 0.50]
			Package 3	trapmf	[0.45, 0.50, 0.65, 0.70]
			Package 4	trapmf	[0.65, 0.70, 1, 1]

The membership functions of the output variable Y are presented in Figure 2.

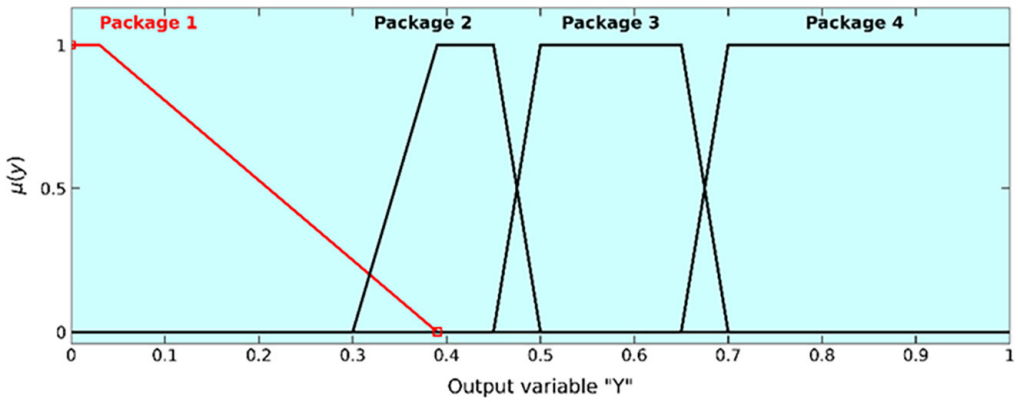


Fig. 2. Membership functions of the output variable Y

Rule base construction. The rule base was constructed from combinations of the linguistic terms of the three input variables. Since each input variable consisted of three linguistic terms, the complete Cartesian product of the input states contained $3 \times 3 \times 3 = 27$ combinations. Each rule had the following structure:

$$R_r: \textit{IF } X_1 \textit{ is } A_r \textit{ AND } X_2 \textit{ is } B_r \textit{ AND } X_3 \textit{ is } C_r \textit{ THEN } Y \textit{ is } D_r, \ldots$$

where A_r, B_r, and C_r denote the linguistic terms of the input variables in rule r, and D_r denotes the corresponding educational package.

The consequents of the 27 rules were established collectively by three teachers holding the qualification category "teacher-expert," who subsequently participated in the experimental evaluation. The experts jointly reviewed the complete rule base and assigned the educational package for each combination of subject knowledge, English language proficiency, and digital competence, taking into account the levels considered necessary for successful completion of the corresponding package. The final consequents were determined through joint discussion and agreement among the three experts. The complete rule base was finalized before the experimental evaluation, and no rule consequents were modified after the study outcomes became available.

The educational rationale was that lower or uneven combinations of the three learner characteristics required a more supportive package, whereas stronger combined profiles allowed assignment to more advanced packages; intermediate combinations were assigned to Packages 2 or 3 according to the complete rule base provided in Supplementary File S4.

Mamdani fuzzy inference. The model employed the Mamdani fuzzy inference mechanism with the following parameters: AND operator – minimum; OR operator – maximum; implication method – minimum; aggregation method – maximum; defuzzification method – centroid.

For the input vector

$$x = (x_1, x_2, x_3)$$

the rule firing strength of rule r was calculated using the minimum operator:

$$\alpha_r = min\left\{\mu_{A_r}(x_1), \mu_{B_r}(x_2), \mu_{C_r}(x_3)\right\}$$

The obtained firing strength truncated the membership function of the output linguistic term associated with the corresponding rule:

$$\mu_r(y) = min\left\{\alpha_r, \mu_{D_r}(y)\right\}$$

The outputs of all activated rules were aggregated using the maximum operator:

$$\mu_{agg}(y) = max_{r=1,\ldots,27}\, \mu_r(y)$$

Thus, the final fuzzy output set combined the recommendations of all rules activated by the given combination of learner characteristics.

Defuzzification and educational package selection. After aggregation of the output fuzzy sets, the crisp output value Y^* of the output variable Y was calculated using the centroid defuzzification method:

$$Y^* = \frac{\int_0^1 y\mu_{agg}(y)dy}{\int_0^1 \mu_{agg}(y)dy},$$

where y is the value of the output variable and $\mu_{agg}(y)$ is the aggregated membership function of the output variable.

To assign the result to one of the four educational packages, the degree of membership of Y^* to each output membership function was calculated:

$$P^* = arg\,max\,\mu_{Pp}(Y^*), p \in \{1,2,3,4\},$$

where P^* denotes the recommended educational package, p is the package index, and $\mu_{Pp}(Y^*)$ is the membership degree of the crisp output value with respect to the corresponding output membership function. The recommended educational package was the one whose membership function attained the maximum value for the obtained crisp output value Y^*. The numerical parameters of the membership functions are presented in Table 3, whereas the complete set of 27 production rules and the MATLAB FIS configuration are provided in Supplementary File S4.

2.5 Use of artificial intelligence tools

ChatGPT (OpenAI) was used for language editing, translation of selected text fragments from Kazakh into English, and graphical preparation of the authors' diagrams and architectural schemes. All scientific content, data analysis, results, and conclusions were developed and verified by the authors.

2.6 Ethical considerations

The study was conducted with permission from the administrations of the participating schools. Before the experimental period began, the required school-level procedures for learner participation were completed. Informed consent from the parents or legal guardians of minor learners was obtained by January 5, 2026. Separate formal assent forms were not collected from minor participants. In accordance with the participating schools' procedures, the signed consent forms were retained securely by the schools' psychological services. Permission from the administrations of the participating schools was obtained before the experimental period began on January 6, 2026. The Ethics Committee determination was not obtained as prospective approval before the study began. A preliminary study report was submitted to the Ethics Committee of D. Serikbayev East Kazakhstan Technical University on May 18, 2026, while the experimental period was ongoing. Following review of the submitted materials, the Committee issued Ethics Committee Determination No. 345 dated May 30, 2026, the final day of the reported experimental period. Accordingly, the determination is reported as a post-study institutional ethics determination and is not described as prospective ethical approval.

3 PLATFORM ARCHITECTURE AND IMPLEMENTATION

The developed platform is an adaptive web-based educational system designed to support personalized learning pathways, providing browser-based access from desktop computers, tablets, and smartphones.

The platform integrates learner profiling, digital competence assessment, AHP-based weighting, and fuzzy-inference-based recommendation. Learning management systems provide digital environments for organizing and supporting educational processes [19], [20]. The proposed platform extends this functionality by generating personalized recommendations based on learners' subject knowledge, English language proficiency, and digital competence. The overall architecture of the platform is presented in Figure 3. The architecture represents the complete educational data processing cycle, from constructing the learner's digital profile and assessing digital competencies to generating personalized educational recommendations and analyzing learning outcomes.

The proposed architecture follows a modular design and consists of several interconnected functional subsystems. The learner profiling subsystem is responsible for collecting and storing user information, including prior knowledge assessment results, digital competence indicators, English language proficiency, and learning history. Based on these data, a learner's digital profile is created and subsequently used to support adaptive educational decision-making. The central component of the architecture is the intelligent decision-support module, which integrates AHP-based criteria weighting with the Mamdani fuzzy inference mechanism. The interaction among these modules enables the automatic generation of personalized educational recommendations.

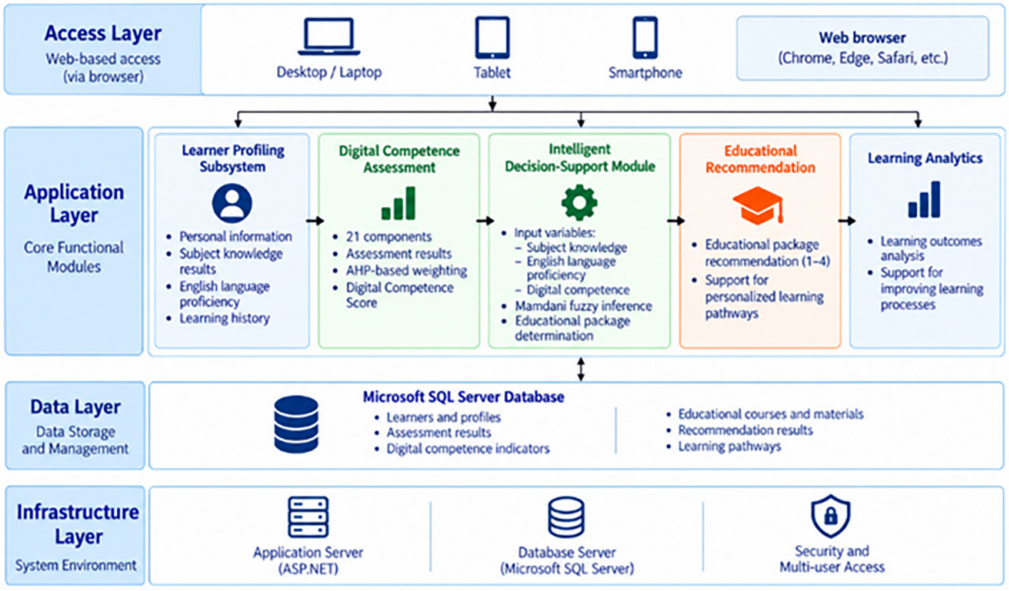


Fig. 3. General architecture of the intelligent personalized learning platform

The digital competence assessment subsystem processes assessment results and calculates the integrated Digital Competence Score using AHP-derived weights. The fuzzy inference subsystem uses subject knowledge, English language proficiency, and digital competence to determine the appropriate educational package based on the Mamdani rule base. The adaptive recommendation subsystem generates educational package recommendations and supports personalized learning pathways according to the generated recommendation. A relational Microsoft SQL Server database is used for data storage. The logical structure of the database is presented in Figure 4. The presented Entity–Relationship (ER) diagram illustrates the logical data structure and the relationships among the main entities of the

educational platform. The database stores information on learners and their profiles, profile indicators, educational courses and packages, competencies, learning tasks, resources, and related educational entities. This structure provides centralized data storage and supports the operation of the platform's intelligent modules. The main functional modules of the platform are presented in Table 4.

Table 4. Functional modules of the adaptive personalized learning platform

Platform Module	Purpose and Main Functions
Learner profiling subsystem	Collects and stores learner information, including learning outcomes, digital competence indicators, subject knowledge, and English language proficiency.
Digital competence assessment subsystem	Processes assessment results, calculates the integrated Digital Competence Score, and constructs the learner's digital profile.
Fuzzy inference subsystem	Analyzes learner input variables, executes Mamdani fuzzy inference rules, and generates intelligent educational recommendations.
Adaptive recommendation subsystem	Generates personalized educational package recommendations and supports personalized learning pathways.
Data storage and management subsystem	Stores information on learners, educational courses, assessment results, recommendations, and learning pathways using Microsoft SQL Server.
Web access subsystem	Provides browser-based access from desktop computers, tablets, and smartphones.

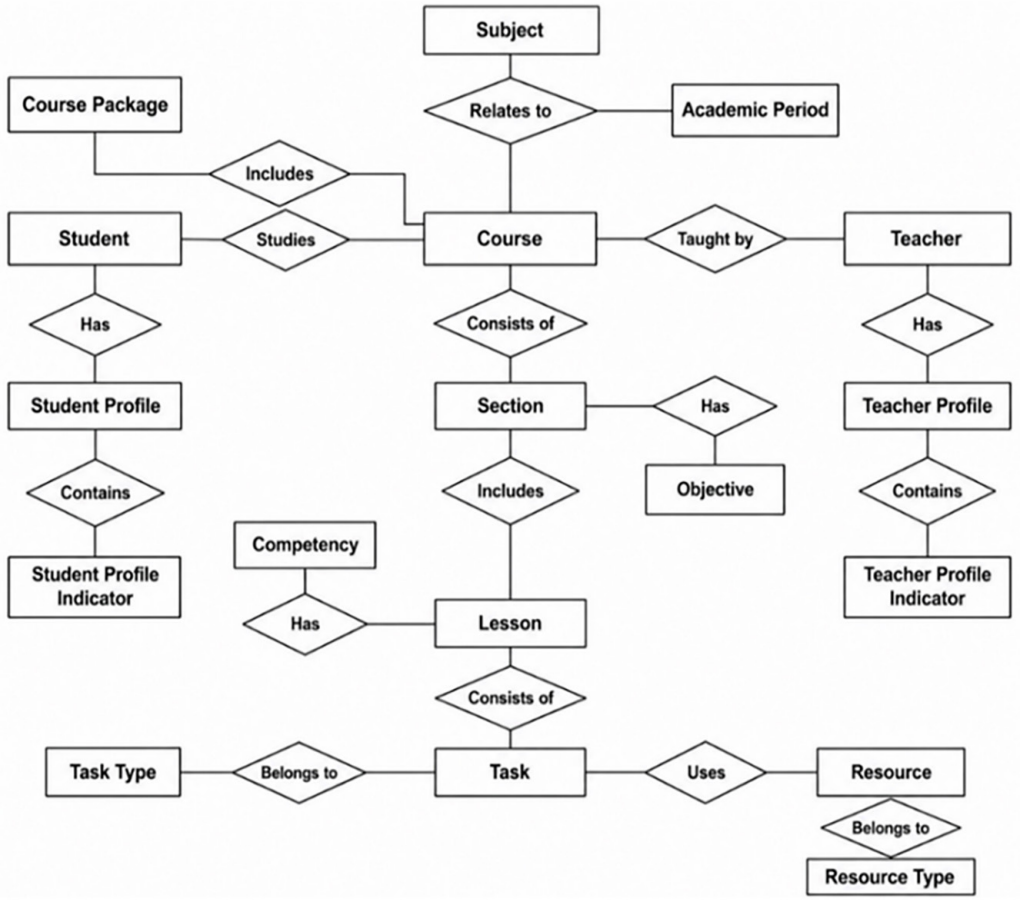


Fig. 4. ER diagram of the personalized learning platform database

The platform was implemented using ASP.NET and Microsoft SQL Server with support for multi-user operation and integration of the developed functional modules.

4 RESULTS

The platform was developed during 2024–2026, and its experimental evaluation was conducted using a quasi-experimental design at two Nazarbayev Intellectual Schools (Astana and Ust-Kamenogorsk) between 6 January and 30 May 2026 (20 weeks, the second academic semester). The aim of the evaluation was to compare the outcomes associated with the use of the developed platform.

The study involved 129 learners in Grades 11–12 from six intact classes across two schools. The assignment was performed at the level of existing school classes in order to preserve the natural educational setting. The experimental group included 67 learners from three intact classes (one class in Astana and two classes in Ust-Kamenogorsk), whereas the control group comprised 62 learners from three intact classes (one class in Astana and two classes in Ust-Kamenogorsk). Within each school, intact classes from the same grade level with comparable prior academic performance were selected, after which the selected classes were randomly allocated to the experimental or control condition. Individual learners were not randomly assigned or transferred between classes.

The package recommendation was generated once, after completion of the initial learner assessments, and was not recalculated during the intervention. Learners had access only to the recommended package and could select among the three courses available within that package; switching between packages was not permitted. Teachers could view learner profiles and course progress and could add instructional materials to their courses but did not modify the automatically assigned package. In the control group, learners selected elective courses without automated personalized recommendations.

The intervention was implemented within elective courses for upper-secondary learners. The intervention lasted 20 weeks and comprised two 60-minute elective-course lessons per week, corresponding to 40 lessons (40 contact hours) per class over the experimental period. The course library comprised four educational packages, each containing three courses of a comparable level representing different profile areas, including chemical-biological, physical-mathematical, and engineering orientations. Each course consisted of sections and lessons comprising targeted competencies, instructional content, and learning tasks. In the experimental group, learners' subject knowledge, English language proficiency, and digital competence were processed by the fuzzy inference model to assign one of the four educational packages. Learners accessed the recommended package and selected one of its three profile-oriented courses. Learning included digital instructional materials, reinforcement and self-assessment tasks, practical and laboratory activities, and formative and summative assessment under teacher supervision.

Instruction was delivered by three teachers holding the qualification category "teacher-expert," each of whom taught both experimental and control classes within his or her school. Before the intervention, the participating teachers received training in the technical use of the platform and in the organization of course content within the developed system. Compliance with the experimental procedures was monitored by school administrators and teachers using class schedules and

LMS records on learner activity, task completion, course participation, and assessment attempts.

A substantial deviation was defined as an unreplaced scheduled lesson, access to a non-assigned educational package, teacher modification of the automatically assigned package, or a sustained technical interruption preventing planned platform use. The available schedules and LMS records indicated that the planned instructional schedule was completed in all six classes, with no package switching, teacher overrides, or other substantial deviations from the planned intervention procedure recorded.

Before the beginning of the experimental period, baseline subject knowledge, English language proficiency, and digital competence were assessed using their original measurement scales. Subject knowledge was expressed as the percentage of correctly completed tasks (0–100%), English language proficiency was assessed on a seven-point scale (0–7), and the integrated Digital Competence Score was expressed on the interval [0, 1]. Descriptive statistics for the experimental and CG are presented in Table 5, including sample size, mean, standard deviation (SD), median, interquartile range (IQR), and observed range. Corresponding class-level descriptive statistics are provided in Supplementary File S5.

Table 5. Baseline characteristics of the experimental (EG) and CG

Baseline Indicator	Group	n	Mean ± SD	Median (IQR)	Range
Subject knowledge (%)	EG	67	70.04 ± 11.60	69.0 (15.0)	46–97
	CG	62	68.71 ± 12.95	69.5 (20.75)	45–91
English language proficiency (0–7)	EG	67	4.07 ± 2.20	4.0 (4.0)	1–7
	CG	62	3.97 ± 1.95	4.0 (3.75)	1–7
Digital Competence Score (0–1)	EG	67	0.518 ± 0.179	0.48 (0.31)	0.24–0.85
	CG	62	0.510 ± 0.180	0.48 (0.265)	0.22–0.86

The baseline subject-knowledge assessment and the final assessment were different assessments covering different content. The baseline assessment measured learners' initial subject knowledge, whereas the final assessment evaluated the content completed during the 20-week course. Therefore, the two assessments were not treated as directly comparable pre- and post-intervention measures, and baseline subject-knowledge scores were not included as a covariate in the final outcome analysis.

Because the study included only six intact classes, reliable cluster-adjusted or multilevel inference was not considered feasible. Accordingly, the individual-level statistical analyses reported below are exploratory and unadjusted for within-class clustering. The findings should therefore be interpreted with consideration of possible class-, school-, teacher-, and intervention-condition effects, which cannot be securely separated in the present design.

4.1 Functional verification of the recommendation model

The recommendation model was functionally verified by analyzing the operation of the Mamdani fuzzy inference mechanism using the rule base comprising 27

production rules described in Section 2.4. The fuzzy inference surface generated in MATLAB is presented in Figure 5.

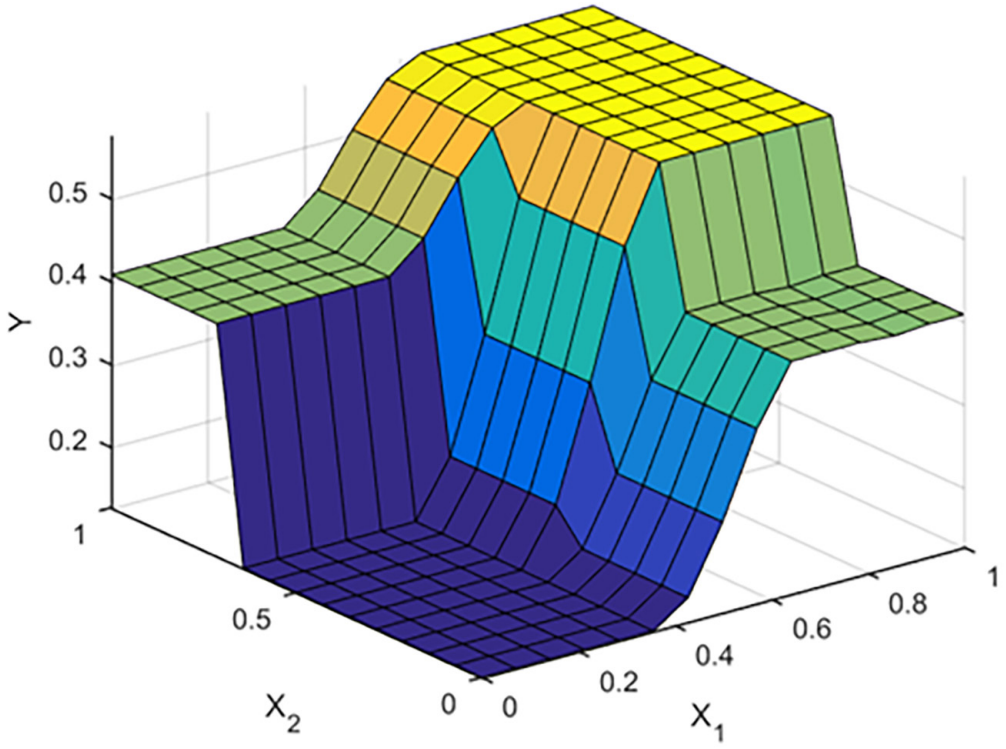


Fig. 5. Fuzzy inference surface for subject knowledge (X_1) and English language proficiency (X_2), with the Digital Competence Score (X_3) fixed at 0.5

The fuzzy inference surface illustrates how the crisp output value varies across combinations of subject knowledge (X_1) and English language proficiency (X_2), with the Digital Competence Score (X_3) fixed at 0.5. To functionally verify the model, representative decision-making scenarios were analyzed. For example, for the input values X_1 = 0.879 (subject knowledge), X_2 = 0.655 (English language proficiency), and X_3 = 0.791 (Digital Competence Score), the system generated the crisp output value Y* = 0.82, corresponding to the recommendation of Educational Package 4. Additional functional verification scenarios, including single-rule cases and cases located in boundary and overlapping membership regions, are presented in Table 6.

Table 6. Functional verification scenarios for the fuzzy recommendation model

Scenario	X_1	X_2	X_3	Activated Rule(s)	Y*	Selected Package
Existing example	0.879	0.655	0.791	1–7, 13	0.8165	Package 4
Single-rule case	0.200	0.200	0.200	27	0.1307	Package 1
Single-rule case	0.600	0.350	0.650	13	0.5750	Package 3
Overlap case	0.850	0.675	0.750	1–7, 13	0.7312	Package 4
Boundary/ overlap case	0.500	0.325	0.600	13, 14, 17, 18, 23, 24, 26, 27	0.3471	Package 2

The expected outputs were determined from the specified 27-rule base and the Mamdani FIS configuration reported in Section 2.4 and Supplementary File S4. No failed cases were observed among the verification scenarios presented in Table 6. This verification assessed conformity between the implemented system and the specified fuzzy rule base rather than the pedagogical quality or external validity of the recommendations.

4.2 Comparative analysis of learning outcomes

To compare learning outcomes between the experimental and CG, final assessment results were analyzed using the original assessment scores and the predefined achievement threshold. The final assessment consisted of practical tasks designed to evaluate mastery of the competencies specified in the course. Scores were expressed as percentages ranging from 0 to 100%, and achievement of at least 70% was defined as successful attainment of the final assessment threshold. The ≥70% criterion had been established before the analysis on the basis of expert evaluation by teachers. The same final assessment procedure, scoring scale, and ≥70% achievement criterion were applied to both the experimental and CG. The final assessment was administered at the end of the 20-week experimental period and was graded using anonymized learner codes; therefore, assessors were blinded to group allocation during grading.

User perceptions of the platform were assessed separately using an author-developed 10-item questionnaire administered between 20 and 27 May 2026, near the end of the 20-week experimental period. The same questionnaire was administered to both groups. However, because several items referred specifically to functions of the developed platform, which the control group had not used, control-group responses to these items were not considered interpretable for between-group comparison. Therefore, questionnaire-based comparisons between the experimental and CG were removed from the inferential analysis, and questionnaire findings are reported descriptively for the experimental group only.

The questionnaire consisted of 10 statements organized into two thematic domains: Learning Satisfaction (SAT_1–SAT_5) and Interaction Quality (INT_1–INT_5). These domains were used only to organize the questionnaire items and were not established or analyzed as validated psychometric scales. Responses were analyzed at the individual-item level using the original five-point Likert scale (1 = strongly disagree; 5 = strongly agree). For each item, the distribution across all five response categories, together with the median and IQR, is reported for the experimental group. Because completion of all questionnaire items was mandatory, no missing responses occurred. The complete questionnaire and the procedures for its administration and data processing are provided in Supplementary File S6.

As the principal analysis, final assessment scores were analyzed in their original percentage form. Because the score distribution in the control group deviated from normality, the experimental and CG were compared using the Mann–Whitney U test. Descriptive statistics included the mean, SD, median, and IQR. In addition, achievement of the predefined ≥70% threshold was analyzed as a secondary exploratory binary outcome using Pearson's χ^2 test, with Cramer's V reported as the effect-size measure. Differences were considered statistically significant at $p < 0.05$. No final assessment scores were missing or excluded. Because allocation occurred at the level of six intact classes, these individual-level inferential analyses did not

account for within-class clustering and are therefore reported as exploratory and unadjusted. Given the small number of classes, no cluster-adjusted inferential model was fitted.

Descriptive statistics for the original final assessment scores and the proportions of learners achieving the predefined ≥70% threshold are presented in Table 7.

Table 7. Final assessment results of the experimental (EG) and CG

Outcome	EG (n = 67)	CG (n = 62)
Mean score ± SD, %	80.97 ± 11.33	79.37 ± 13.79
Median (Q1–Q3), %	81.0 (73.0–90.5)	81.0 (67.25–90.75)
Score range, %	55–100	55–100
Achievement of ≥70% threshold, n/N (%)	60/67 (89.6%)	45/62 (72.6%)

The original final assessment scores were compared between the experimental and CG using the Mann–Whitney U test. In addition, achievement of the predefined ≥70% threshold was examined as a secondary exploratory binary outcome using Pearson's χ^2 test. The results of these statistical comparisons are presented in Table 8.

Table 8. Statistical comparison of final assessment results between the groups

Outcome	Statistical Test	Statistic	p-Value	Effect Size
Final assessment score (%)	Mann–Whitney U	2176.5	0.641	–
Achievement of the predefined ≥70% final-assessment threshold	Pearson's χ^2	6.12	0.013	Cramer's V = 0.218

The principal analysis of the original final assessment scores showed no statistically significant difference between the experimental and CG (Mann–Whitney U = 2176.5, p = 0.641). The median score was 81% in both groups, although the distributions differed in their IQRs. In the secondary exploratory threshold-based analysis, 60 of 67 learners (89.6%) in the experimental group and 45 of 62 learners (72.6%) in the control group achieved the predefined ≥70% threshold. In the exploratory individual-level threshold analysis, this difference yielded $\chi^2 = 6.12$, p = 0.013, and Cramer's V = 0.218; however, this comparison was not adjusted for allocation through intact classes.

Class-level descriptive analysis showed that the proportion of learners achieving the predefined ≥70% threshold was higher in the experimental class than in the corresponding control class for all three class pairs, although differences in the original final assessment scores were not uniform across classes. Detailed class-level results are provided in Supplementary File S7.

Questionnaire responses from the experimental group are presented descriptively in Table 9. These results represent users' perceptions of specific aspects of their experience with the platform and should not be interpreted as objective measures of platform effectiveness or as between-group evidence.

Table 9. Experimental-group responses to individual user-perception items (n = 67)

Item	1, n (%)	2, n (%)	3, n (%)	4, n (%)	5, n (%)	Median	IQR
SAT_1—Recommendations helped understanding	0 (0.0%)	3 (4.5%)	5 (7.5%)	29 (43.3%)	30 (44.8%)	4	1
SAT_2—Interface and navigation were convenient	0 (0.0%)	4 (6.0%)	15 (22.4%)	38 (56.7%)	10 (14.9%)	4	1
SAT_3—Platform increased motivation	0 (0.0%)	4 (6.0%)	16 (23.9%)	9 (13.4%)	38 (56.7%)	5	2
SAT_4—Learning at own pace was more comfortable	0 (0.0%)	3 (4.5%)	4 (6.0%)	30 (44.8%)	30 (44.8%)	4	1
SAT_5—Satisfaction with platform learning experience	0 (0.0%)	3 (4.5%)	3 (4.5%)	20 (29.9%)	41 (61.2%)	5	1
INT_1—Teacher feedback based on platform data was timely and useful	3 (4.5%)	9 (13.4%)	13 (19.4%)	31 (46.3%)	11 (16.4%)	4	1
INT_2—Platform facilitated interaction with teacher	1 (1.5%)	4 (6.0%)	15 (22.4%)	9 (13.4%)	38 (56.7%)	5	2
INT_3—Digital tools facilitated peer collaboration	0 (0.0%)	8 (11.9%)	20 (29.9%)	34 (50.7%)	5 (7.5%)	4	1
INT_4—Adaptive tasks encouraged discussion with teacher	3 (4.5%)	7 (10.4%)	9 (13.4%)	33 (49.3%)	15 (22.4%)	4	1
INT_5—Academic support and classroom interaction improved	1 (1.5%)	3 (4.5%)	3 (4.5%)	31 (46.3%)	29 (43.3%)	4	1

Experimental-group responses were predominantly concentrated in the upper response categories for several questionnaire items. The highest median ratings were observed for SAT_3 (perceived motivation), SAT_5 (satisfaction with the platform learning experience), and INT_2 (perceived facilitation of interaction with the teacher), each with a median of 5. The remaining items had a median of 4. These findings represent item-level user perceptions among learners who used the platform and were not used for inferential comparisons with the control group.

5 DISCUSSION

The principal analysis showed that the original final assessment scores did not differ significantly between the experimental and CG. However, in the secondary exploratory threshold-based analysis, which was not adjusted for allocation through intact classes, a significantly higher proportion of learners in the experimental group achieved the predefined ≥70% final-assessment threshold. Experimental-group questionnaire responses also indicated generally positive perceptions of the platform, although these findings were descriptive and were not used for between-group comparisons.

Digital competence was incorporated as one of the three learner-profile inputs, alongside subject knowledge and English language proficiency. This design is consistent with the role of digital competence in digital learning environments [1].

Particular attention should be given to the performance of the recommendation mechanism. The use of Mamdani fuzzy inference enabled recommendations to be

generated based on multiple interrelated factors without rigid discrete partitioning of input values during recommendation generation. Functional verification showed that the implemented mechanism produced outputs consistent with the specified fuzzy rule base across the examined scenarios. This verification assessed the functional conformity of the implemented mechanism and should not be interpreted as independent validation of recommendation quality. These findings indicate the potential of interpretable fuzzy models for educational recommendation systems and are consistent with recent studies applying fuzzy approaches to course and teaching-resource recommendation [16], [17].

The use of explicit expert-defined rules makes the recommendation process interpretable and allows its decision logic to be examined directly. However, the consequents of the 27-rule base were defined through expert judgment by the same three teacher-experts who participated in the educational implementation. Although the rules were jointly reviewed and finalized before the experiment, the rule-construction process was not independently validated by an external expert panel. This limits the extent to which the resulting rule base can be generalized beyond the present implementation context. The practical significance of the study lies in the potential application of the platform to support personalized learning in the context of the digital transformation of education and the development of digital competencies. More broadly, recent bibliometric evidence identifies mobile devices, blended learning, digital literacy, and flexible access as recurring themes in the development of mobile learning in higher education [21].

The limitations of the study include the relatively small sample and, more importantly for the study design, the small number of participating clusters (six intact classes across two schools), the use of a fixed set of input variables, and the absence of long-term monitoring of educational outcomes. In addition, the Digital Competence Score was derived from the author-developed 210-item Digital Competence Assessment Instrument, which received only a practical pilot administration involving three students and did not undergo formal psychometric validation or reliability assessment; therefore, the Digital Competence Score should be regarded as an operational measure used in this implementation rather than as a validated measure of digital competence.

The AHP procedure also has limitations. The original individual and aggregated pairwise-comparison matrices were not retained in a form permitting independent reconstruction of the reported priority weights and consistency statistics. Consistency was assessed only for the aggregated matrices; individual participant matrices were not separately evaluated, and the influence of potentially inconsistent individual judgments on the aggregated priorities is therefore unknown. No separate higher-level comparison of the five competence groups was conducted; the retained local priorities were pooled and re-normalized without additional group-level weights to construct the integrated Digital Competence Score. No sensitivity analysis was performed for the NPV ≥ 0.10 selection threshold; therefore, the stability of component selection under alternative thresholds remains unknown.

The questionnaire also had an important limitation for between-group interpretation. The same questionnaire was administered to both groups, but several items referred specifically to platform-related experiences that were not equivalent for the control group. Therefore, between-group inferential comparisons of questionnaire responses were not retained, and the experimental-group responses were interpreted descriptively only. A further ethical limitation is that separate formal assent was not obtained from minor participants, although parental or legal-guardian consent and school permission were obtained before the intervention began.

Furthermore, because the intervention was implemented in six intact classes across two schools and the individual-level analyses were not adjusted for within-class clustering, class-, school-, teacher-, and intervention-condition effects cannot be securely separated. Therefore, the inferential findings should be interpreted as exploratory associations rather than evidence of causal effects.

The study did not record the types of devices used by learners, the proportion of sessions completed on smartphones or tablets, or the frequency of mobile access. Therefore, mobile access should be regarded as a technical implementation feature of the web-based platform rather than as an empirically evaluated component of the intervention. Future research will focus on extending the learner model and further developing the recommendation mechanism.

6 CONCLUSION

An adaptive web-based platform was developed to support personalized learning. The proposed model considers subject knowledge, English language proficiency, and digital competence, enabling the construction of personalized learning pathways.

The developed platform architecture integrates learner profiling, digital competence assessment, and rule-based educational recommendation. Mamdani fuzzy inference provided an explicit rule-based mechanism for combining the three learner-profile inputs into educational package recommendations.

The principal analysis of the original final-assessment scores showed no statistically significant difference between the experimental and CG. However, in the secondary exploratory analysis, a significantly higher proportion of learners in the experimental group achieved the predefined ≥70% final-assessment threshold (89.6% vs. 72.6%, $p = 0.013$, Cramer's $V = 0.218$); this individual-level threshold analysis was not adjusted for allocation through intact classes, and this result should be interpreted cautiously because class-, school-, teacher-, and intervention-condition effects cannot be securely separated. Experimental-group questionnaire responses indicated generally positive perceptions of several aspects of platform use; these findings were descriptive and were not used for between-group comparisons.

Taken together, these exploratory findings indicate the potential of interpretable rule-based recommendation mechanisms for adaptive web-based platforms supporting personalized learning but do not establish a causal intervention effect. Future research will focus on extending the learner model and further developing the platform's functionality.

7 REFERENCES

[1] R. Vuorikari, S. Kluzer, and Y. Punie, *DigComp 2.2: The Digital Competence Framework for Citizens – With New Examples of Knowledge, Skills and Attitudes*. Luxembourg: Publications Office of the European Union, 2022. https://doi.org/10.2760/115376

[2] H. A. Alamri, S. Watson, and W. Watson, "Learning technology models that support personalization within blended learning environments in higher education," *TechTrends*, vol. 65, no. 1, pp. 62–78, 2021. https://doi.org/10.1007/s11528-020-00530-3

[3] Hariyanto, F. X. D. Kristianingsih, and R. Maharani, "Artificial intelligence in adaptive education: A systematic review of techniques for personalized learning," *Discover Education*, vol. 4, Art. no. 458, 2025. https://doi.org/10.1007/s44217-025-00908-6

[4] W. Strielkowski, V. Grebennikova, A. Lisovskiy, G. Rakhimova, and T. Vasileva, "AI-driven adaptive learning for sustainable educational transformation," *Sustainable Development*, vol. 33, no. 2, pp. 1921–1947, 2025. https://doi.org/10.1002/sd.3221

[5] D. Y. Long, S. Wang, S. Md Rashid, and X. T. Lu, "Artificial intelligence in higher education: A systematic review of its impact on student engagement and the mediating role of teaching methods," *Frontiers in Education*, vol. 10, Art. no. 1648661, 2026. https://doi.org/10.3389/feduc.2025.1648661

[6] L. Y. Tan, S. Hu, D. J. Yeo, and K. H. Cheong, "Artificial intelligence-enabled adaptive learning platforms: A review," *Computers and Education: Artificial Intelligence*, vol. 9, Art. no. 100429, 2025. https://doi.org/10.1016/j.caeai.2025.100429

[7] E. H. Mamdani, "Application of fuzzy algorithms for control of simple dynamic plant," *Proceedings of the Institution of Electrical Engineers*, vol. 121, no. 12, pp. 1585–1588, 1974. https://doi.org/10.1049/piee.1974.0328

[8] T. T. Ramanath and M. J. Hossen, "Incremental learning based fuzzy reasoning approach for diagnosis of thyroid disease," *Bulletin of Electrical Engineering and Informatics*, vol. 14, no. 4, pp. 2793–2806, 2025. https://doi.org/10.11591/eei.v14i4.9140

[9] Z. Seitakhmetova, U. A. Tulkibaevna, A. Sadvakassova, A. Ikenova, R. Karmenova, and G. Zhunussova, "Determining university students' views on mobile technology and Moodle applications in personalized learning," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 16, no. 23, pp. 59–72, 2022. https://doi.org/10.3991/ijim.v16i23.36207

[10] S. Yaghmour, M. I. Qureshi, I. Ullah, R. K. Perumal, and M. M. Khan, "AI-driven adaptive learning systems in mobile education: A systematic review of personalization strategies, effectiveness, and user interaction," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 19, no. 19, pp. 70–86, 2025. https://doi.org/10.3991/ijim.v19i19.57695

[11] L. Li, "Virtualized and personalized financial management education enabled by mobile interactive technologies," *International Journal of Interactive Mobile Technologies (iJIM)*, vol. 20, no. 8, pp. 103–117, 2026. https://doi.org/10.3991/ijim.v20i08.61249

[12] C. Redecker, *European Framework for the Digital Competence of Educators: DigCompEdu*, Y. Punie, Ed. Luxembourg: Publications Office of the European Union, 2017. https://doi.org/10.2760/159770

[13] N. Kerimbayev, Z. Umirzakova, R. Shadiev, and V. Jotsov, "A student-centered approach using modern technologies in distance learning: A systematic review of the literature," *Smart Learning Environments*, vol. 10, Art. no. 61, 2023. https://doi.org/10.1186/s40561-023-00280-8

[14] A. Mendekenova, Z. Aukhadieva, and D. Zhanikeyeva, "Beyond the hype: AI outperforms VR/AR and gamification in foreign language education," *Journal of Information Technology Education: Innovations in Practice*, vol. 24, p. 29, 2025. https://doi.org/10.28945/5665

[15] Z. Zulpykhar, K. Kariyeva, A. Sadvakassova, R. Zhilmagambetova, and S. Nariman, "Assessing the effectiveness of personalized adaptive learning in teaching mathematics at the college level," *International Journal of Engineering Pedagogy (iJEP)*, vol. 15, no. 4, pp. 4–22, 2025. https://doi.org/10.3991/ijep.v15i4.52797

[16] M. P. Shareef, B. Roslind, and J. Mathew, "FESSARec: Explaining course recommendations using fuzzy expert system and self-attention," *International Journal of Data Analysis Techniques and Strategies*, vol. 16, no. 2, pp. 207–221, 2024. https://doi.org/10.1504/IJDATS.2024.137870

[17] H. Shen, "Design of teaching resource recommendation platform based on fuzzy recommendation algorithm in the context of education informatization," *KSII Transactions on Internet and Information Systems*, vol. 18, no. 11, pp. 3129–3147, 2024. https://doi.org/10.3837/tiis.2024.11.002

[18] T. L. Saaty, *The Analytic Hierarchy Process: Planning, Priority Setting, Resource Allocation*. New York, NY, USA: McGraw-Hill, 1980.

[19] S. Noreen, "Implementation of learning management system: A way ahead on the digital journey in distance learning," *Open Praxis*, vol. 12, no. 3, pp. 329–342, 2020. https://doi.org/10.5944/openpraxis.12.3.1086

[20] OECD, *OECD Digital Education Outlook 2023: Towards an Effective Digital Education Ecosystem*. Paris: OECD Publishing, 2023. https://doi.org/10.1787/c74f03de-en

[21] A. D. Samala, S. Papadakis, and S. Rawas, "Global insights into mobile learning in higher education: A PRISMA-guided bibliometric analysis from 2007 to 2023," *International Journal of Educational Reform*, 2025. https://doi.org/10.1177/10567879251341869

8 AUTHORS

Zhanat Seitakhmetova, PhD in Information Systems, is an Associate Professor at the Department of Information Technologies and Artificial Intelligence, Sarsen Amanzholov East Kazakhstan University, Ust-Kamenogorsk, Kazakhstan. Her research interests include digital competence modeling, personalized learning, educational information systems, mobile technologies, and digital educational platforms (E-mail: jseitahmetova@eku.kz).

Zhalgasbek Iztayev, a Candidate of Pedagogical Sciences, is an Associate Professor of Computer Science at the Higher School of Computer Engineering and Energetic, M. Auezov, South Kazakhstan University, Shymkent, Kazakhstan. His research interests include computer science education, programming languages, optimization methods, and computer and mathematical modeling (E-mail: zhalgasbek.iztaev@auezov.edu.kz).

Kamalbek Berkimbayev, Doctor of Pedagogical Sciences, is a Professor at Khoja Akhmet Yassawi International Kazakh-Turkish University, Turkestan, Kazakhstan. His research interests focus on pedagogy, educational technologies, and the development of innovative approaches to education (E-mail: kamalbek.berkimbaev@ayu.edu.kz).

Egemberdy Tenizbaev, a Candidate of Technical Sciences, is an Associate Professor and Head of the Department of Technics and Information Technologies at Central Asian Innovation University in Shymkent, Kazakhstan. He is also a full member of the International Academy of Informatization (E-mail: tenizbaev_egemberdi@portal.caiu.edu.kz).

Symbat Nurgaliyeva, PhD in Computer Science, is an Assistant Professor at the School of Software Engineering, Astana IT University, Astana, Kazakhstan. Her research focuses on improving the quality of education for future computer science teachers through the theoretical and practical integration of robotics technologies, with particular emphasis on the use of mobile robots in the educational process. Her scientific interests include educational robotics, mobile robot development, machine learning, and neural networks (E-mail: symbat.nurgaliyeva@astanait.edu.kz).

Zhanbota Bakytova is a student at Nazarbayev Intellectual School of Physics and Mathematics, Astana, Kazakhstan. Her research interests include computer science, artificial intelligence, software engineering, machine learning, and the development of digital solutions for education (E-mail: baqytova_zh@ast.nis.edu.kz).