Developing a Digital Learning Platform for Blended Integrative Instruction: An ADDIE-based Design and Feasibility Study

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***Abstract*—The rapid advancement of digital technologies has significantly transformed higher education, necessitating pedagogically grounded platforms that support integrative and blended instructional approaches. However, while numerous Learning Management System (LMS) solutions exist, empirical studies on platforms that systematically integrate instructional design frameworks with adaptive learning mechanisms remain limited, particularly within digitally transforming educational contexts. This study presents the design, development, and expert-based feasibility evaluation of the Integrative Digital Learning Platform (IDLP), a modular system built to support blended integrative instruction in higher education. The platform is grounded in the Analysis, Design, Development, Implementation, and Evaluation (ADDIE) instructional design framework and the People, Process, Product (P3) model, incorporating pedagogical approaches including Technological Pedagogical Content Knowledge (TPACK), competency-based learning, and backward design. Technically, the system employs Django Rest Framework as the backend, Vue.js 3 as the frontend, and PostgreSQL as the database, featuring six core modules: user and role management, course and content delivery, automated assessment, learning analytics, Artificial Intelligence (AI)-driven recommendations, and resource management. Feasibility was evaluated through structured expert review and user feedback involving 66 participants across three roles: administrators (n = 1), instructors (n = 9), and students (n = 56). Results confirmed high levels of functional reliability, pedagogical alignment, and usability across all user groups. The findings suggest that purposefully designed, modular platforms grounded in established instructional design principles can serve as a feasible and pedagogically grounded basis for supporting integrative blended instruction, and underscore the need for further empirical validation in diverse higher education contexts.**

***Keywords*—digital learning platform, integrative instruction, blended learning, ADDIE, People, Process, Product (P3) model, higher education**

I. Introduction

The rapid digitalization of higher education has fundamentally reshaped the ways in which instruction is designed, delivered, and evaluated. As educational institutions increasingly adopt technology-enhanced learning environments, the demand for platforms capable of supporting complex pedagogical approaches—including integrative and blended forms of instruction—has grown considerably [1, 2]. Integrative instruction, which emphasizes the interconnection of knowledge domains, competency development, and learner-centered engagement, represents one of the most pedagogically demanding approaches to implement in digital contexts [3, 4]. Blended learning, combining face-to-face and online modalities, has emerged as a widely adopted model in higher education due to its flexibility and effectiveness in accommodating diverse learner needs [5, 6].

While existing platforms such as Moodle, Canvas, and Blackboard offer broad functionality, studies indicate that they are often deployed primarily for content delivery and assessment management, with limited built-in support for integrative instructional design frameworks, adaptive learning mechanisms, and role-differentiated pedagogical environments [7–9]. Furthermore, the majority of existing platforms follow a one-size-fits-all architecture that limits their capacity to support differentiated instructional strategies or personalized learning pathways [9–11].

Instructional design frameworks such as Analysis, Design, Development, Implementation, and Evaluation (ADDIE) provide systematic guidance for developing effective learning environments [12]. The P3 model—encompassing People, Process, and Product dimensions—offers an organizational lens for ensuring that platform development addresses not only technical functionality but also human and procedural factors [13]. However, while these frameworks are well established in the literature, their integration into the architectural design of digital learning platforms remains insufficiently explored, particularly in the context of integrative blended instruction [14, 15].

A growing body of research highlights the potential of AI-driven recommendation systems and learning analytics in enhancing personalized learning experiences within digital platforms [16, 17]. Real-time monitoring of learner behavior, adaptive content delivery, and data-informed feedback have been identified as key affordances of intelligent learning environments [18]. Nevertheless, empirical studies

examining platforms that systematically combine these intelligent features with established instructional design models—particularly within higher education contexts undergoing digital transformation—remain limited [19, 20].

To address this gap, the present study presents the design, development, and feasibility evaluation of the Integrative Digital Learning Platform (IDLP), based on expert review and user feedback. The platform is a modular system grounded in the ADDIE framework and the P3 model, incorporating six functional modules—user and role management, course and content delivery, automated assessment, learning analytics, AI-driven recommendations, and resource management—and is implemented using Django Rest Framework, Vue.js 3, and PostgreSQL.

The study is guided by the following research questions:

(1) How can the ADDIE instructional design framework and the P3 model be operationalized in the architectural design of a modular digital learning platform?
(2) To what extent does the developed platform demonstrate functional reliability, pedagogical alignment, and usability across different user roles?
(3) In what ways does the integration of AI-driven recommendations and learning analytics support personalized and integrative blended instruction?

Although existing learning management systems such as Moodle, Canvas, and Blackboard provide comprehensive support for course administration, content delivery, and assessment, they generally treat instructional design, learning analytics, and AI-based personalization as independent or optional components. In contrast, the proposed Integrative Digital Learning Platform (IDLP) was designed around a unified pedagogical architecture in which instructional design principles govern the organization of platform functionality. Rather than simply incorporating ADDIE, the P3 model, learning analytics, and AI-driven recommendations as separate features, the platform operationalizes these components into a coherent instructional workflow that supports adaptive blended learning. The study contributes to the field in three ways. First, it offers a replicable framework for developing pedagogically grounded digital platforms by integrating ADDIE and P3 principles into platform architecture. Second, it provides feasibility evidence from a higher education context undergoing digital transformation, informing platform development practice in similar settings. Third, it demonstrates how intelligent technologies—including AI recommendations and learning analytics—can be meaningfully embedded within an instructional design framework to support integrative blended learning.

II. Literature Review

The development of digital learning platforms has been extensively studied in the context of higher education transformation. Benavides *et al.* [1] and Haleem *et al.* [2] demonstrate that institutional adoption of digital platforms extends beyond mere content digitization, encompassing structural changes in pedagogical practices, organizational workflows, and learner-instructor interaction models. Within this broader landscape, Learning Management Systems have historically served as the primary infrastructure for online and blended instruction. However, as Alseelawi *et al.* [7] illustrate in their ADDIE-based e-learning platform development study, effective digital platform design demands more than functional completeness—it requires deliberate alignment between technical architecture and instructional design principles. The limitations of general-purpose platforms in supporting role-differentiated, pedagogically grounded instruction have been further documented by Timotheou *et al.* [8], who identify the absence of adaptive mechanisms and instructional framework integration as persistent gaps in current LMS deployments.

Modular software architecture has emerged as a widely adopted approach for addressing the scalability and flexibility demands of educational platforms. Newman [21] establishes the theoretical foundation for microservices-based architectures, emphasizing the advantages of service independence, maintainability, and horizontal scalability in multi-user systems. Complementing this, Pahl and Jamshidi [22] provide empirical evidence that modular architectures outperform monolithic designs in educational technology contexts requiring frequent updates and role-based differentiation. The modular monolithic approach—which preserves a unified codebase while organizing functionality into discrete, independently developable modules—has been proposed by Su and Li [23] as a pragmatic intermediate architecture particularly suited to small-to-medium educational platform development. In the present study, this approach is operationalized through a Django Rest Framework backend, Vue.js 3 frontend, and PostgreSQL database, with each functional domain implemented as an independent module communicating via standardized Rest APIs [24, 25].

The ADDIE instructional design framework provides the methodological backbone for the platform's pedagogical architecture [12]. Branch [12] articulates ADDIE as a cyclical process encompassing analysis of learner needs, design of instructional objectives, development of learning materials, implementation within authentic educational contexts, and evaluation of outcomes—a sequence directly reflected in the platform's development lifecycle. The P3 model proposed by Khan [13] further extends this framework by foregrounding the human and organizational dimensions of e-learning development, positioning People, Process, and Product as co-equal determinants of platform success. The integration of these two frameworks within a unified platform architecture represents a theoretical contribution of the present study, as existing literature treats them predominantly as separate design considerations [7, 12].

Learning analytics and AI-driven recommendation systems constitute a rapidly expanding domain within educational technology research. Brusilovsky's [16] foundational work on adaptive hypermedia establishes the core mechanisms—user modeling, adaptive presentation, and adaptive navigation—through which digital platforms can respond dynamically to individual learner profiles. Siemens and Long [17] further position learning analytics as an essential affordance of intelligent learning environments, enabling real-time monitoring of learner behavior and data-informed instructional adjustment. Roll and Wylie [18] demonstrate that AI-supported systems can identify knowledge gaps, provide adaptive feedback, and personalize learning trajectories at scale—capabilities that remain largely absent from conventional LMS platforms. In the IDLP, these

capabilities are implemented through an integrated AI recommendation module that analyzes assessment performance data to generate personalized content and resource suggestions, supported by a learning analytics dashboard providing real-time visibility into learner progress across all user roles [26, 27].

Data security and access control represent critical dimensions of digital platform design in higher education contexts. Role-Based Access Control (RBAC), as documented by Salunke *et al.* [28], provides a structured mechanism for enforcing differentiated access privileges across administrator, instructor, and student roles—a feature directly implemented in the IDLP through JSON Web Token (JWT)-based authentication and RBAC authorization layers [29]. Database integrity and normalization, governed by the relational principles articulated by Codd [30] and further elaborated by Silberschatz *et al*. [31], underpin the platform's PostgreSQL-based data management architecture, ensuring consistency, minimizing redundancy, and supporting efficient query processing across concurrent user sessions.

Collectively, the literature reveals a consistent and significant gap. Although ADDIE-based platform development [7], P3 model applications [13], learning analytics [17], and AI-driven recommendation systems [16, 18] are individually well documented, their systematic integration within a single pedagogically grounded platform architecture remains insufficiently explored. Existing general-purpose LMS platforms such as Moodle, Canvas, and Blackboard primarily support content delivery, assessment management, and communication; however, they do not operationalize instructional design frameworks as governing architectural principles, nor do they embed role-differentiated pedagogical environments within a unified theoretical model [7, 9]. Previous ADDIE-based platform development studies have generally applied ADDIE as a procedural development methodology, guiding the sequential stages of analysis, design, development, implementation, and evaluation, rather than as a structural logic that directly shapes a platform's functional modules, role-based workflows, content hierarchy, and adaptive feedback mechanisms [7]. Similarly, AI-driven recommendation systems and learning analytics have often been studied as standalone technical features [16–18], without systematic grounding in an instructional design framework that governs their pedagogical logic and integration. The present study addresses this gap by operationalizing ADDIE and the P3 model simultaneously as architectural principles within the IDLP. In this platform, ADDIE structures the instructional design logic, the P3 model organizes the People, Process, and Product dimensions, and AI-driven recommendations function as an adaptive feedback mechanism connected to learning analytics. Thus, the novelty of the study lies not in the separate use of ADDIE, P3, or AI-based recommendations, but in their integrated operationalization within a modular digital learning platform designed to support blended integrative instruction. This constitutes the primary theoretical and practical contribution of the present study.

More specifically, the proposed platform differs from existing adaptive learning environments in three aspects. First, ADDIE is operationalized not only as a development methodology but also as the architectural logic governing user roles, instructional workflows, learning resources, assessment processes, and feedback mechanisms. Second, the AI recommendation module combines semantic concept extraction using a Large Language Model (LLM), knowledge graph construction, and learner analytics within a single adaptive pipeline. Third, recommendations are generated based not only on learner performance but also on concept-level knowledge gaps identified through relationships between instructional resources and extracted concepts. These characteristics distinguish the proposed platform from conventional LMS implementations and existing adaptive recommendation approaches.

III. Materials and Methods

A. Research Design and Approach

This study employed a design-based research approach grounded in the ADDIE instructional design model and the P3 framework (People, Process, Product) to guide the systematic development and feasibility evaluation of the Integrative Digital Learning Platform (IDLP) [12, 13]. The research design integrates technical platform development with structured pedagogical evaluation, reflecting the dual nature of the IDLP as both a software artifact and an instructional tool. Feasibility was assessed across three dimensions—functional reliability, pedagogical alignment, and usability—through structured instruments administered to three distinct user groups. The study is positioned within the broader context of higher education digital transformation in Uzbekistan, where institutional demand for pedagogically grounded, modular learning platforms continues to grow [19, 20].

B. Platform Architecture and Technical Development

The IDLP was developed using a modular monolithic architecture [23], comprising three primary layers: a frontend presentation layer implemented in Vue.js 3 [32], built using Vite [33], with Tailwind CSS, a backend application layer built on Django Rest Framework, and a data storage layer powered by PostgreSQL (see Fig. 1). Inter-layer communication is handled through RESTful APIs, with Role-Based Access Control (RBAC) enforced via JSON Web Token (JWT) authentication across three user roles: administrator, instructor, and student [28, 29].

The platform incorporates six core functional modules, each implemented as an independent component within the application layer. The first module, user and role management, governs system-wide access control by assigning and enforcing differentiated permissions across administrator, instructor, and student roles through RBAC and JWT-based authentication. The organizational structure of the platform spans four hierarchical levels: university, faculty, department, and individual user, enabling context-aware role assignment and institutional data separation.

The second module, course and content delivery, is structured around a subject-topic-resource hierarchy. Each subject is assigned defined credit hours and linked to a specific department, while topic organization supports six

instructional types: lecture, practical, independent study, laboratory, seminar, and other. Subject-to-group assignment is managed through a four-way linkage connecting subjects, student groups, semester periods, and responsible instructors within a single relational structure, ensuring accurate course scheduling and instructor accountability. Each topic supports nine resource formats: presentations, videos, documents, quizzes, tests, practical files, practical assignments, AI-generated content, and other supplementary materials, providing instructors with a comprehensive content authoring environment [26, 27].

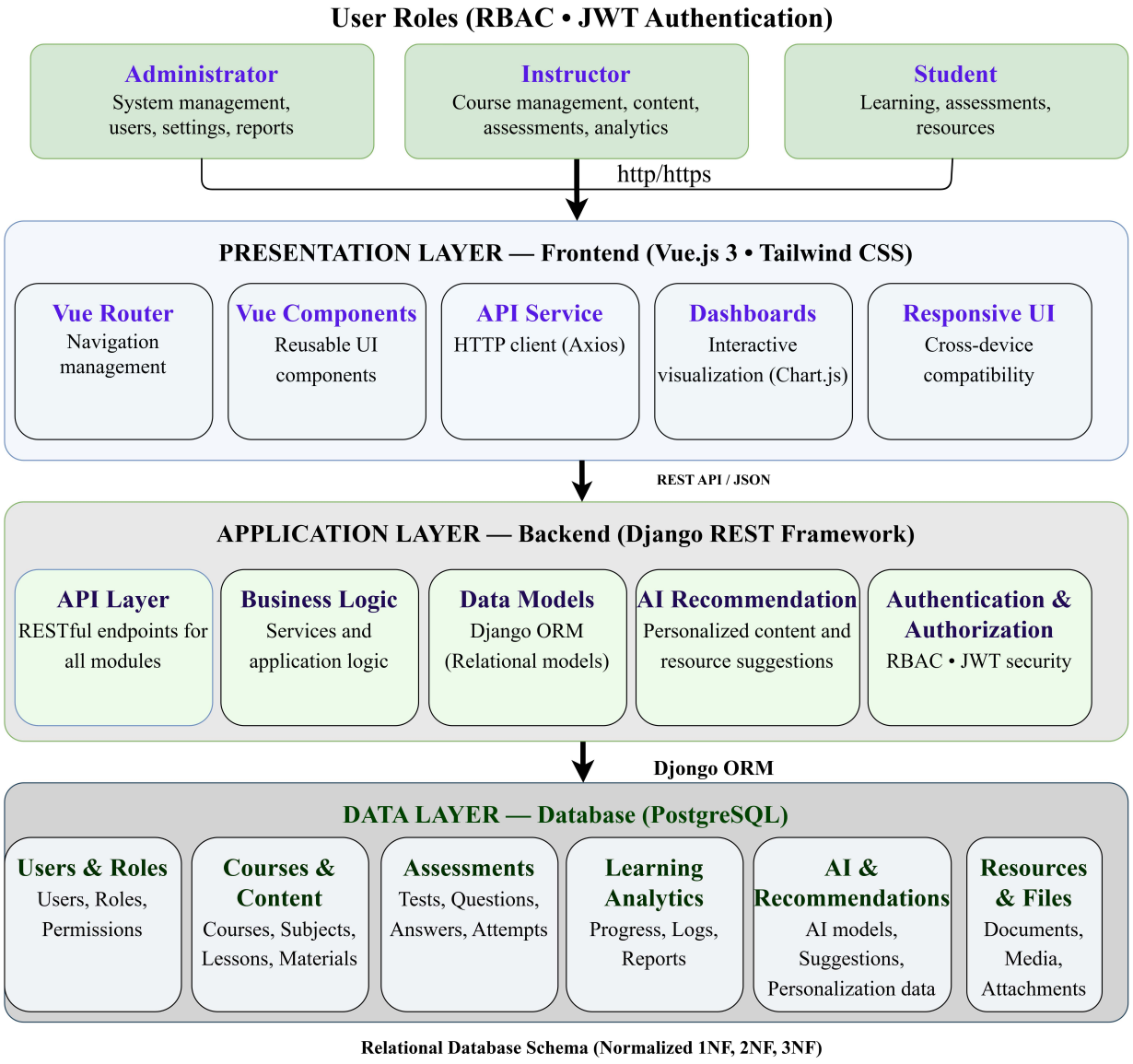


Fig. 1. Three-layer modular architecture of the IDLP.

The third module, automated assessment, supports six assessment categories: lecture test, practical test, midterm examination, final examination, quiz, and independent study test. Each assessment comprises questions of three configurable types—multiple choice, single choice, and text input, with automatic scoring applied upon submission. Every learner attempt is independently stored with its date, score, and individual answer selections, maintaining a complete and auditable assessment history for each participant [30].

The fourth module, learning analytics, provides real-time visibility into learner engagement at the topic level. Nine distinct engagement indicators are tracked per learner per topic: lecture viewed, lecture resources viewed, practical completed, independent study resources viewed, lecture test passed, practical test passed, independent study test passed, overall score, and engagement duration in seconds across three activity types. Individual resource-level engagement is additionally recorded, capturing viewing duration and access status per item to support fine-grained behavioral analytics. Aggregated progress data are surfaced through role-specific interactive dashboards rendered via Chart.js.

The fifth module, AI-driven recommendations, implements a closed-loop adaptive learning mechanism through a three-stage pipeline [16, 17].

Stage 1. Resource ingestion and AI-based content analysis.

When an instructor uploads a learning resource, the system initiates an automated content analysis process. The AI pipeline extracts semantic content from the uploaded material, identifies key knowledge units embedded within it, and maps their locations within the resource structure. The results are stored as structured data directly within each learning resource record, enabling content-aware recommendation

logic at subsequent stages.

Stage 2. Concept extraction and knowledge graph construction.

Alongside content analysis, the AI pipeline identifies and links the conceptual knowledge items covered by each resource. Each concept represents a discrete, reusable knowledge unit within the subject domain. Through this resource-concept linkage, the platform constructs a topic-level knowledge graph in which each learning resource is semantically anchored to one or more conceptual knowledge items. This structure enables the system to identify not only which resources a learner has accessed, but which specific concepts they have or have not been exposed to, a prerequisite for gap-targeted adaptive recommendations [16].

Stage 3. Personalized recommendation generation.

Drawing on the knowledge graph and the learner's topic-level engagement and assessment data, the AI module generates a personalized recommendation for each student-topic combination. Each recommendation comprises three components: a curated set of suggested learning resources based on prior engagement and performance; a set of conceptual knowledge items targeting identified gaps; and a natural language explanation providing the learner with a rationale for the suggestions. Each recommendation carries an actionable status flag that transitions upon learner engagement, enabling the system to track recommendation effectiveness across the learning cycle [17, 18].

Technically, the AI-driven recommendation module was implemented using the OpenAI GPT-4o large language model accessed through the OpenAI API. The recommendation engine follows an LLM-assisted hybrid approach rather than a purely rule-based or conventional machine-learning-based approach. After textual content was extracted from PDF, DOCX, or PPTX files, the model identified key concepts, generated short descriptions, and returned source-location indicators linking each concept to the original resource. The model was configured with a temperature value of 0.5 to maintain a balance between consistency and semantic flexibility. The model was instructed through a structured prompt specifically designed to extract educational concepts and generate pedagogically appropriate recommendations while maintaining consistency across learning resources. The generated outputs were programmatically validated before being stored in the database: each concept was required to satisfy predefined length constraints, include a non-empty description, and contain a source-location reference. These validated concept–resource relationships were then used to construct the topic-level knowledge graph that supports personalized recommendation generation. Thus, the module combines GPT-4o-based semantic concept extraction with rule-based validation, topic-level knowledge graph construction, and learning analytics-driven personalization to generate context-aware personalized learning recommendations.

The recommendation engine operates through a two-stage adaptive mechanism. In the first attempt, the system applies a rule-based approach by directing the learner to the source location of the incorrectly answered question within the original learning resource, thereby encouraging independent re-engagement with the material without AI-generated explanation. In the second attempt, the GPT-4o model generates a detailed natural-language explanation covering the reason for the learner's error, the correct answer, and a practical illustrative example. Each recommendation is stored with an actionable status flag that transitions upon learner engagement, enabling the system to monitor recommendation uptake across the learning cycle. The AI module was designed to support personalized learning rather than replace instructor judgment.

Through this pipeline, the AI module operates as a formative support mechanism that continuously adapts to each learner's evolving profile without requiring additional instructor intervention [19, 20].

The sixth module, resource management, encompasses the upload, storage, and retrieval of all learning materials. Practical work submission accepts both file-based and text-based student responses, which are subsequently evaluated by an integrated AI mechanism generating an automated score and detailed feedback. This enables timely, consistent, and scalable formative assessment independent of instructor availability [18].

The data storage layer is built on a normalized relational database schema, designed in accordance with first, second, and third normal forms (1NF, 2NF, 3NF) to ensure data integrity, eliminate redundancy, and support efficient concurrent query processing [30, 31].

C. ADDIE-based Development Process

The development of the IDLP was structured according to the five stages of the ADDIE model, integrated with the P3 framework across People, Process, and Product dimensions (see Fig. 2). In the Analysis stage, an examination of existing LMS limitations, institutional learner needs, and pedagogical requirements for integrative blended instruction was conducted to define the functional and technical specifications of the platform [12].

The Design stage produced the three-layer system architecture, a normalized relational database schema, Vue.js 3 component wireframes, and a pedagogical alignment mapping integrating TPACK, competency-based learning, and backward design principles into the platform's instructional structure [13, 14]. The Development stage encompassed full-stack implementation, including Django Rest Framework backend construction, Vue.js 3 frontend component development, PostgreSQL database configuration, Rest API integration, and deployment of the AI recommendation module. The Implementation stage involved platform deployment at Tashkent University of Economics and Pedagogy (TUEP) and structured onboarding of 66 participants, comprising administrator (n = 1), instructors (n = 9), and students (n = 56), into their respective role-differentiated environments. The Evaluation stage collected feasibility data through structured Likert-scale instruments administered across all participant groups, assessing functional reliability, pedagogical alignment, and usability [7, 8].

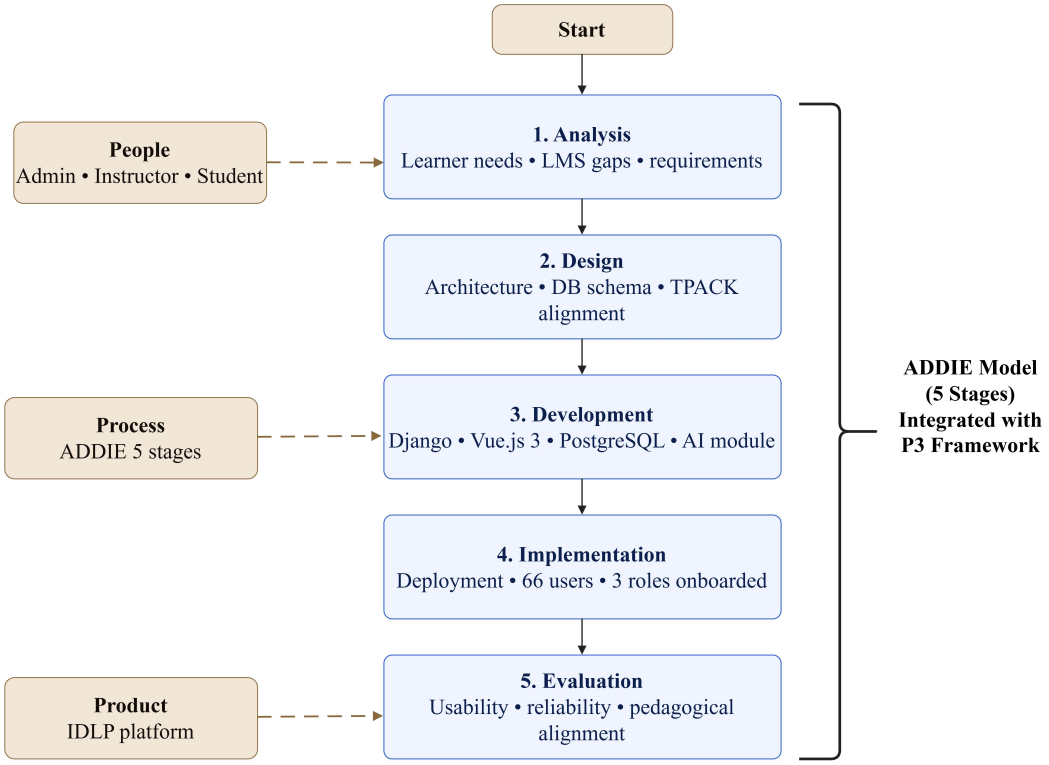


Fig. 2. ADDIE-based development lifecycle integrated with the P3 (People–Process–Product) framework in the IDLP.

D. Participants

Feasibility evaluation was conducted with 66 participants across three user roles: administrator (n = 1), instructors (n = 9), and students (n = 56). Participants were recruited through purposive sampling from Tashkent University of Economics and Pedagogy (TUEP), where the IDLP was introduced as the primary digital learning environment during the study period. Instructors were selected based on their active involvement in course delivery through the platform, while students were drawn from courses in which the IDLP was formally integrated into the instructional process. All participants completed a structured orientation session prior to evaluation to ensure familiarity with the platform's core features and role-specific functionalities. Participation was voluntary, and informed consent was obtained from all participants before data collection commenced. Table 1 summarizes the participant distribution by role.

Table 1. Participant distribution by role

Role	n	Percentage
Administrator	1	1.5%
Instructor	9	13.6%
Student	56	84.8%
Total	66	100%

E. Instruments and Data Collection

Feasibility was evaluated across three dimensions using structured instruments adapted from established platform assessment frameworks [7, 8], each employing a five-point Likert scale (1 = strongly disagree, 5 = strongly agree). The five-point Likert scale was selected for its established reliability and sensitivity in capturing graded responses in platform usability and feasibility research [7, 8]. The functional reliability instrument assessed system stability, module operability, role-based access integrity, and cross-device compatibility. The pedagogical alignment instrument examined the degree to which platform features supported integrative instructional design, learning analytics, and personalized feedback delivery. The usability instrument evaluated interface clarity, navigation intuitiveness, and role-specific dashboard functionality, grounded in Human-Computer Interaction principles [34]. Table 2 presents the evaluation framework.

Table 2. Feasibility evaluation dimensions and instruments

Dimension	Focus areas	Items	Respondents
Functional reliability	System stability, module operability, RBAC integrity	10	All (n = 66)
Pedagogical alignment	ADDIE integration, AI recommendations, analytics	8	Instructor + admin (n = 10)
Usability	Interface clarity, navigation, dashboards	10	All (n = 66)
	Total	28	-

F. Data Analysis

Quantitative data collected through the evaluation instruments were analyzed using descriptive statistics, including Mean scores (M) and Standard Deviations (SD), computed for each evaluation dimension and user role. Internal consistency of the instruments was assessed using Cronbach's Alpha coefficient (α), calculated as follows:

$$\alpha = \frac{k}{k-1}\left(1 - \frac{\sum_{i=1}^{k}\sigma_i^2}{\sigma_t^2}\right)$$

where k denotes the number of items, σ_t^2 denotes the variance of each individual item, and σ_t^2 denotes the total variance of all items combined.

Mean scores were interpreted using descriptive categories adapted from established five-point Likert-scale mean interpretation guidelines proposed by Cenita and Guzman [35] 4.50–5.00 = very high feasibility; 3.50–4.49 = high feasibility; 2.50–3.49 = moderate feasibility; 1.50–2.49 = low feasibility; and 1.00–1.49 = very low feasibility [35].

These categories were used solely to facilitate the interpretation of descriptive findings and should not be interpreted as statistically derived or inferential thresholds. The resulting Cronbach's alpha coefficients were interpreted according to the guidelines proposed by George and Mallery [36]: $\alpha > 0.9$—excellent, $\alpha > 0.8$—good, $\alpha > 0.7$—acceptable, $\alpha > 0.6$—questionable, $\alpha > 0.5$—poor, and $\alpha < 0.5$—unacceptable. All statistical analyses were conducted using SPSS version 26.

Fig. 3 illustrates the complete research workflow from platform development through feasibility evaluation.

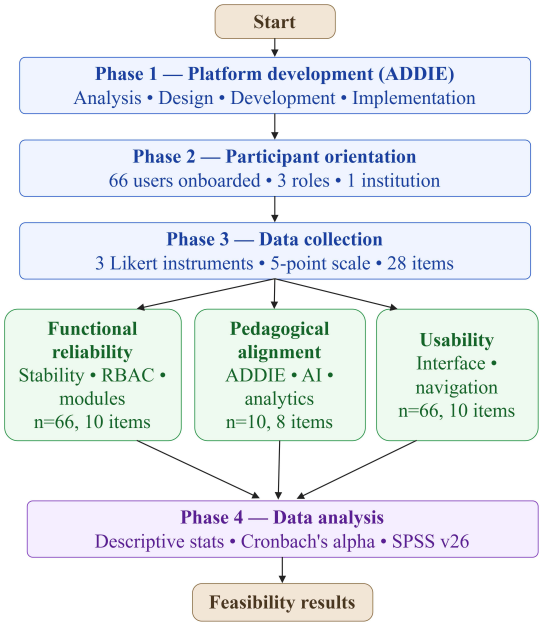


Fig. 3. Research workflow from IDLP development to feasibility evaluation.

G. Ethical Considerations

Ethical approval for this study was obtained from the relevant institutional authority at Tashkent University of Economics and Pedagogy (TUEP). All participants were informed of the research objectives, their right to withdraw at any time, and the confidentiality of their responses. Participation was entirely voluntary, and informed consent was obtained from all participants before data collection commenced. No personally identifiable information was disclosed. Data were used exclusively for research purposes and stored securely in accordance with institutional data protection guidelines. Regarding platform-level data governance, all learner analytics and behavioral engagement data collected through the IDLP are accessible exclusively to authorized users within their role-specific permissions, enforced through the RBAC and JWT-based authentication architecture. Student data are not shared with external parties. The AI-driven recommendation module processes learner engagement and assessment data only within the platform environment to generate personalized learning recommendations, and personally identifiable information is not transmitted outside the institutional deployment context.

IV. Results

A. Instrument Reliability

Prior to reporting descriptive findings, the internal consistency of the three evaluation instruments was assessed using Cronbach's alpha coefficient. The functional reliability instrument yielded $\alpha = 0.812$, indicating good internal consistency. The pedagogical alignment instrument demonstrated strong reliability with $\alpha = 0.883$, while the usability instrument yielded $\alpha = 0.763$, meeting the acceptable threshold for exploratory feasibility research [7, 8]. Table 3 summarizes the reliability coefficients across all three dimensions.

Table 3. Instrument reliability coefficients

Dimension	Items	n	Cronbach's α	Interpretation
Functional reliability	10	66	0.812	Good
Pedagogical alignment	8	10	0.883	Good
Usability	10	66	0.763	Acceptable

B. Functional Reliability

Descriptive analysis of the functional reliability dimension revealed predominantly high feasibility ratings, with an overall mean of $M = 4.13$ (SD = 0.70) (see Table 4). The highest-rated item was S3, which assessed role-based access control integrity, yielding $M = 4.45$ (SD = 0.58). The lowest-rated item was S5, which assessed cross-device compatibility, with $M = 3.44$ (SD = 0.94), falling within the moderate feasibility range. This finding suggests that while core platform functions operate reliably, compatibility across diverse device types and screen sizes requires further technical refinement. Role-based analysis indicated generally consistent ratings: students ($n = 56$) reported $M = 4.10$ (SD = 0.74), instructors ($n = 9$) reported $M = 4.28$ (SD = 0.59), and the administrator ($n = 1$) reported $M = 4.30$.

Table 4. Functional reliability: Mean scores and standard deviations ($n = 66$)

Item	Description	M	SD	Classification
S1	Platform stability	4.38	0.61	High
S2	Module operability	4.21	0.73	High
S3	Role-based access control	4.45	0.58	High
S4	Authentication reliability	4.18	0.69	High
S5	Cross-device compatibility	3.44	0.94	Moderate
S6	Page loading performance	4.29	0.64	High
S7	Cross-module navigation	3.62	0.83	High
S8	Data storage accuracy	4.31	0.65	High
S9	Assessment scoring accuracy	4.19	0.71	High
S10	Progress data visibility	4.26	0.62	High
	Overall	4.13	0.70	High

C. Pedagogical Alignment

The pedagogical alignment dimension, evaluated by instructors and the administrator ($n = 10$), yielded an overall mean of $M = 4.20$ (SD = 0.74), classified as high feasibility (see Table 5). Two items reached the very high feasibility threshold: S1, which assessed ADDIE framework operationalization ($M = 4.60$, SD = 0.52), and S8, reflecting overall support for integrative blended instruction ($M = 4.60$, SD = 0.52). The lowest-rated item was S7, which assessed the instructional alignment of the three-stage AI pipeline, with $M = 3.40$ (SD = 1.02), falling within the moderate feasibility range. The wider standard deviation observed for S7 reflects divergent expert views on the AI module's pedagogical grounding, indicating that further alignment between the AI recommendation logic and established instructional design principles may be warranted in future development cycles.

Table 5. Pedagogical alignment: Mean scores and standard deviations (n = 10)

Item	Description	M	SD	Classification
S1	ADDIE framework operationalization	4.60	0.52	Very high
S2	Topic type diversity	4.30	0.67	High
S3	Resource format flexibility	4.50	0.71	Very high
S4	AI recommendation relevance	4.10	0.74	High
S5	Analytics-informed instruction	4.30	0.82	High
S6	Competency-based learning support	3.80	0.92	High
S7	AI pipeline instructional alignment	3.40	1.02	Moderate
S8	Overall integrative instruction support	4.60	0.52	Very high
	Overall	4.20	0.74	High

D. Usability

The usability dimension yielded an overall mean of M = 3.99 (SD = 0.74) across all 66 participants, classified as high feasibility (see Table 6). The highest-rated item was S10, reflecting overall ease of use, with M = 4.29 (SD = 0.59). Two items fell within the moderate feasibility range: S5, which assessed label and instruction clarity (M = 3.44, SD = 0.98), and S7, which assessed independent task completion without external assistance (M = 3.48, SD = 1.01). The wider standard deviations on these items suggest meaningful variation in participants' digital literacy levels, particularly among student users who may have had limited prior experience with structured digital learning environments. Role-based analysis showed slightly higher ratings among instructors (M = 4.12, SD = 0.68) compared to students (M = 3.97, SD = 0.76) and the administrator (M = 4.00).

Table 6. Usability: Mean scores and standard deviations (n = 66)

Item	Description	M	SD	Classification
S1	Interface clarity	4.15	0.68	High
S2	Navigation intuitiveness	3.98	0.74	High
S3	Dashboard organization	4.21	0.61	High
S4	Feature accessibility	4.09	0.72	High
S5	Label and instruction clarity	3.44	0.98	Moderate
S6	System responsiveness	4.18	0.65	High
S7	Independent task completion	3.48	1.01	Moderate
S8	Analytics visualization clarity	4.02	0.71	High
S9	Design consistency	4.11	0.67	High
S10	Overall ease of use	4.29	0.59	High
	Overall	3.99	0.74	High

E. Summary of Feasibility Findings

Collectively, the results confirm that the IDLP demonstrates high feasibility across all three evaluated dimensions. Pedagogical alignment received the highest mean score (M = 4.20), followed by functional reliability (M = 4.13) and usability (M = 3.99) (see Table 7). Moderate feasibility ratings were observed for cross-device compatibility (S5, FR: M = 3.44), AI pipeline instructional alignment (S7, PA: M = 3.40), and label clarity and independent task completion in the usability dimension (M = 3.44 and M = 3.48, respectively), identifying specific areas for future platform refinement. The overall feasibility mean of M = 4.11 (SD = 0.73) with α = 0.819 indicates that the IDLP is a viable and pedagogically grounded platform for supporting integrative blended instruction in higher education contexts. These findings indicate that while the platform demonstrates strong overall feasibility, targeted improvements in device compatibility, AI alignment, and interface clarity are necessary for broader institutional deployment.

Table 7. Summary of feasibility evaluation results

Dimension	n	M	SD	α	Classification
Functional reliability	66	4.13	0.70	0.812	High
Pedagogical alignment	10	4.20	0.74	0.883	High
Usability	66	3.99	0.74	0.763	High
Overall feasibility	66	4.11	0.73	0.819	High

V. Discussion

A. Findings

The findings of this study address the three research questions guiding the design and feasibility evaluation of the IDLP, and are discussed in relation to the existing literature on digital learning platform development, instructional design, and intelligent learning technologies.

RQ1: ADDIE and P3 operationalization. The first research question examined how the ADDIE instructional design framework and the P3 model could be operationalized within the architectural design of a modular digital learning platform. The development process demonstrated that ADDIE's five stages—analysis, design, development, implementation, and evaluation—can be systematically mapped onto platform development phases, from initial needs analysis through technical implementation to structured feasibility
evaluation [12]. This finding aligns with Branch's [12] articulation of ADDIE as a cyclical, iterative process whose stages constitute design decisions embedded in the platform's architecture. The P3 model's People, Process, and Product dimensions further guided the alignment between user role differentiation, developmental workflow, and final platform functionality [13], consistent with Khan's [13] positioning of P3 as an organizational framework that ensures platform development remains responsive to both human and technical requirements. The high feasibility rating received for ADDIE framework operationalization (S1, PA: M = 4.60) confirms that expert evaluators perceived strong alignment between the platform's design and established instructional design principles, supporting the theoretical contribution of integrating ADDIE and P3 within a unified architectural framework. This finding further supports the theoretical distinction between applying ADDIE as a procedural development guide—as documented in prior ADDIE-based platform implementations [7]—and operationalizing it as an architectural principle governing the platform's functional structure. Unlike general-purpose LMS platforms such as Moodle and Canvas, which support content delivery without embedding instructional design frameworks as architectural logic [7, 9], the IDLP positions ADDIE and P3 as co-equal structural principles governing both technical architecture and pedagogical implementation. This distinction represents the primary theoretical advancement of the present study over existing platform development approaches [7, 12].

RQ2: Functional reliability, pedagogical alignment, and usability. The second research question addressed the degree to which the developed platform demonstrates feasibility across the three evaluated dimensions. Overall feasibility was confirmed at the high level across all dimensions (FR: M = 4.13; PA: M = 4.20; US: M = 3.99), consistent with findings from comparable platform evaluation studies that report mean feasibility scores in the 3.90–4.50 range for purpose-built educational platforms [7, 8]. The strong

performance on functional reliability—particularly for role-based access control (S3, M = 4.45) and data storage accuracy (S8, M = 4.31)—reflects the robustness of the IDLP's RBAC and JWT-based security architecture, consistent with Salunke *et al.*'s [28] documentation of RBAC as a reliable mechanism for enforcing differentiated access in multi-role educational systems. However, the moderate rating observed for cross-device compatibility (S5, FR: M = 3.44) indicates that the platform's frontend requires further optimization for mobile and tablet devices—a limitation consistent with Timotheou *et al.*'s [8] observation that cross-device accessibility remains a persistent challenge in LMS deployments. These findings suggest that while the platform's core technical infrastructure is sound, targeted interface and compatibility refinements are necessary before large-scale institutional deployment.

The moderate ratings observed for cross-device compatibility (S5, FR: M = 3.44), label and instruction clarity (S5, US: M = 3.44), and independent task completion (S7, US: M = 3.48) identify specific usability dimensions requiring targeted attention prior to large-scale deployment. Cross-device compatibility limitations reflect the platform's current optimization for desktop environments and indicate that mobile and tablet interface refinement is a development priority. The moderate ratings for label clarity and independent task completion, accompanied by wider standard deviations, suggest variation in participants' digital literacy levels and highlight the need for improved onboarding support and interface guidance to facilitate independent platform engagement across diverse user populations.

RQ3: AI-driven recommendations and learning analytics. The third research question investigated the degree to which the integration of AI-driven recommendations and learning analytics supports personalized and integrative blended instruction. The moderate feasibility rating for AI pipeline instructional alignment (S7, PA: M = 3.40, SD = 1.02)—accompanied by the widest standard deviation across all evaluated items—suggests that while expert evaluators recognized the conceptual value of the three-stage AI pipeline, opinions diverged regarding its current degree of alignment with established instructional design principles. This finding is consistent with Roll and Wylie's [18] observation that AI-supported educational systems demonstrate strong adaptive potential but frequently require iterative refinement of their recommendation logic to achieve meaningful pedagogical alignment. Conversely, the high ratings received for analytics-informed instruction (S5, PA: M = 4.30) and AI recommendation relevance (S4, PA: M = 4.10) indicate that participants perceived the platform's learning analytics dashboard and recommendation outputs as pedagogically relevant and informative, supporting Siemens and Long's [17] positioning of learning analytics as a key affordance of intelligent learning environments. These findings collectively suggest that the IDLP's intelligent features represent a promising foundation for personalized integrative instruction, while highlighting the need for continued development of the AI module's instructional alignment mechanisms.

To further clarify the contribution of the IDLP, a structured qualitative benchmark was conducted against widely used learning management systems, including Moodle, Canvas, and Blackboard. The purpose of this comparison was not to claim that the IDLP replaces these established systems, but to identify the specific pedagogical and architectural dimensions in which the proposed platform differs from general-purpose LMS solutions. Existing LMS platforms provide strong support for content delivery, assessment management, communication, and course administration. However, they are generally not designed around ADDIE as a governing architectural principle, do not explicitly embed the P3 model as an organizational framework, and do not systematically connect AI-driven recommendations with instructional design logic, knowledge graph construction, and adaptive feedback mechanisms. In contrast, the IDLP was developed as a purpose-built platform in which instructional design, role-differentiated implementation, learning analytics, and personalized recommendations are integrated within a unified modular architecture (see Table 8).

Table 8. Qualitative comparison of IDLP with existing LMS platforms

Comparison dimension	Moodle/Canvas/Blackboard	IDLP
Main design orientation	General-purpose LMS for course management, content delivery, assessment, and communication	Purpose-built platform for blended integrative instruction
ADDIE integration	May be used externally as a course design guide	Operationalized as an architectural and pedagogical structuring principle
P3 model integration	Not explicitly embedded as a platform-level framework	Embedded through People, Process, and Product dimensions
Role differentiation	Standard administrator, teacher, and student roles	Role-differentiated pedagogical workflows and dashboards
Learning analytics	Available partially depending on platform and plugins	Integrated as a core module connected to learner engagement and assessment data
AI-driven recommendation	Usually plugin-based or external	Built into the platform as a core adaptive support mechanism
Knowledge graph support	Not typically embedded as a native feature	Concept–resource links form a topic-level knowledge graph
Integrative blended instruction	Supported indirectly through course tools	Supported directly through instructional design, content hierarchy, analytics, and recommendations
Competency-based assessment	Possible through configuration	Embedded into the platform's pedagogical alignment and assessment structure
Instructional design governs system architecture	Not embedded	Core architectural principle
Semantic concept extraction from resources	Not available natively	Implemented via GPT-4o
Topic-level knowledge graph	Not available	Concept–resource graph constructed automatically
Concept-gap identification	Not available	Identified through knowledge graph analysis
Explainable AI recommendations	Plugin-based only	Built-in natural language rationale
Closed-loop adaptive recommendation	Not available	Tracks recommendation effectiveness per learner

This qualitative benchmark indicates that the IDLP's contribution lies not in offering more general LMS functions, but in integrating instructional design logic, organizational role differentiation, analytics, and AI-supported adaptive feedback within one coherent platform architecture. Therefore, the IDLP should be understood as a purpose-built pedagogical platform for blended integrative instruction rather than as a conventional course management system.

B. Novelty and Contribution of the Proposed Platform

The principal contribution of the proposed platform lies in its architectural and pedagogical operationalization rather than in the individual technologies employed. ADDIE, the P3 model, learning analytics, and AI-assisted recommendations have each been reported separately in previous studies. However, existing LMS platforms generally implement these elements independently or through external plugins without establishing explicit pedagogical relationships among them. In the IDLP, instructional design governs the organization of learning resources, assessment, analytics, recommendation generation, and user interaction within one coherent instructional architecture.

Furthermore, unlike conventional adaptive learning systems that primarily recommend learning materials based on previous learner behavior or assessment scores, the proposed recommendation mechanism integrates semantic concept extraction, topic-level knowledge graph construction, learner engagement analytics, and assessment performance into a unified recommendation process. This enables the system to identify concept-level learning gaps and provide targeted instructional recommendations together with explanatory feedback. Consequently, the proposed platform contributes not only a modular software architecture but also a pedagogically grounded adaptive recommendation framework.

C. Generalizability and Implementation Considerations

Although the present study was conducted within a single higher education institution, the proposed IDLP was intentionally designed using platform-independent technologies and pedagogically grounded instructional principles. Therefore, the overall architecture is not institution-specific and may be adapted to other higher education environments with similar instructional requirements. The platform's multi-level organizational hierarchy spanning university, faculty, department, and group enables deployment across multiple institutions within a single server environment without requiring separate technical configurations for each institution.

Nevertheless, successful implementation in other institutions may depend on contextual factors such as institutional digital transformation policies, instructors' digital competence, students' digital literacy, administrative support, curriculum structure, and local pedagogical practices. These contextual variables should be considered when transferring the platform to different educational environments, particularly in contexts with different levels of digital infrastructure or varying institutional approaches to blended and integrative instruction.

From a technical perspective, implementation requires a stable internet connection, a web server capable of hosting the Django Rest Framework backend and PostgreSQL database, modern web browsers for client access, and administrative support for platform maintenance. When AI-driven recommendation and content analysis features are enabled, an active OpenAI API subscription is required. Because the platform follows a modular architecture, additional AI services or institutional LMS components may be integrated with only minor modifications to the existing platform architecture.

Although the present evaluation was based primarily on structured feasibility questionnaires, the IDLP continuously records objective system-generated data, including login frequency, learning resource access, assessment attempts, engagement duration, recommendation status, and task completion events through its learning analytics module. These behavioral indicators were not analyzed in the present study because the primary objective was to evaluate the platform's initial feasibility rather than learner performance or system effectiveness. Future studies will integrate these objective usage metrics with subjective evaluation results to provide a more comprehensive assessment of platform performance.

Consequently, the findings of the present study should be interpreted as evidence of initial feasibility rather than universal effectiveness across higher education institutions. Multi-institutional validation remains an important direction for future research.

D. Limitations

Several limitations of this study warrant acknowledgment. First, the purposive sample drawn from a single institution (TUEP) limits the generalizability of the feasibility findings to other higher education contexts, particularly those with different levels of digital infrastructure or institutional digital literacy. Second, the pedagogical alignment dimension was evaluated by a small expert group (n = 10), comprising nine instructors and one administrator recruited through purposive sampling from a single institution—Tashkent University of Economics and Pedagogy (TUEP). While this approach ensured that evaluators possessed direct, role-specific platform experience—a methodological requirement of expert-based feasibility assessment [7, 12]—it constrains the statistical robustness and generalizability of findings in this dimension. In addition, the uneven role distribution and small expert sample limited the appropriateness of inferential statistical procedures such as group comparisons, correlation analysis, or predictive testing in the present feasibility phase. The pedagogical alignment results should therefore be interpreted as perceived expert feasibility evidence rather than evidence of instructional effectiveness. Future studies should incorporate larger, multi-institutional samples and apply inferential statistical procedures where appropriate to strengthen the reliability, validity, and transferability of the findings. Third, as a feasibility evaluation rather than an efficacy study, the present research does not provide empirical evidence of the platform's direct impact on student learning outcomes including academic performance, retention rates, or comparative effectiveness relative to existing platforms. The reported Likert-scale results should therefore be interpreted as evidence of perceived feasibility, not as evidence of improved learning outcomes. A follow-up quasi-experimental study measuring pre- and post-learning

performance, engagement analytics, and comparisons between experimental and control groups is planned as the next research phase.

A further limitation concerns the evaluation of the AI-driven recommendation module. Although the module was implemented and assessed as part of the overall feasibility evaluation, the present study did not include quantitative recommendation-quality metrics such as precision, recall, F1-score, relevance ranking, or comparison with baseline recommendation methods. Therefore, the reported AI-related feasibility result (M = 3.40) should be interpreted as perceived instructional alignment rather than as technical validation of recommendation performance. Future research will evaluate the AI module through expert-validated concept extraction accuracy, learner and instructor relevance ratings, agreement analysis between AI-generated recommendations and instructor judgments, and comparative testing against rule-based or non-personalized baseline recommendation approaches.

Another limitation concerns the absence of formal triangulation between subjective feasibility ratings and objective system-generated data. Although the IDLP includes a learning analytics module that records learner engagement indicators, resource access status, viewing duration, assessment completion, and activity duration, these behavioral data were not statistically analyzed in the present feasibility evaluation. Therefore, the findings should be interpreted primarily as perceived feasibility evidence rather than as a comprehensive evaluation of actual usage behavior or instructional effectiveness. Future research will incorporate objective platform analytics, including usage logs, task completion time, engagement duration, access frequency, assessment attempts, and behavioral interaction patterns,
to strengthen the validity of the evaluation through mixed-methods triangulation.

Another limitation is that usability was evaluated through users' perceived experiences collected using Likert-scale questionnaires rather than objective usability testing methods. The present study did not measure task completion time, task success rate, navigation errors, or other standardized usability indicators. Future evaluations will incorporate task-based usability testing and objective human-computer interaction metrics to complement perception-based findings and strengthen the evidence regarding platform usability.

Additionally, formal psychometric validation procedures-including item-total correlation analysis, confidence interval estimation, Exploratory Factor Analysis (EFA), Confirmatory Factor Analysis (CFA), and convergent or discriminant validity testing-were not conducted in the present study. Although the evaluation instruments were adapted from established educational platform assessment frameworks [7, 8] and were theoretically grounded in the ADDIE and P3 models, comprehensive psychometric validation was beyond the scope of this initial feasibility study. Future large-scale investigations will incorporate these analyses to further strengthen the validity, reliability, and measurement properties of the evaluation instruments.

Finally, the exploratory nature of the current feasibility study underscores the need for further empirical validation through large-scale implementation across multiple institutional contexts. Despite these limitations, the findings provide a strong foundation for the continued development and empirical validation of pedagogically grounded digital learning platforms in higher education.

VI. Conclusion

This study presented the design, development, and feasibility evaluation of the Integrative Digital Learning Platform (IDLP), a modular system developed to support blended integrative instruction in higher education. The platform is grounded in the ADDIE instructional design framework and the P3 model, enabling the alignment of pedagogical principles with system architecture.

Feasibility was evaluated across three dimensions—functional reliability, pedagogical alignment, and usability—using structured Likert-scale instruments administered to 66 participants across three user roles at Tashkent University of Economics and Pedagogy (TUEP). The findings indicate high overall feasibility, with mean scores of M = 4.13 for functional reliability, M = 4.20 for pedagogical alignment, and M = 3.99 for usability, resulting in an overall feasibility mean of M = 4.11 (α = 0.819).

The results further demonstrate that the platform successfully operationalizes established instructional design principles within a modular digital environment. High ratings for ADDIE framework implementation and integrative blended instruction support confirm the strength of the platform's pedagogical foundation, while moderate ratings for cross-device compatibility, AI pipeline alignment, and selected usability factors highlight areas requiring targeted refinement prior to large-scale deployment.

This study contributes to the field in two significant ways. First, it provides a replicable design framework that integrates ADDIE and P3 principles into the architectural development of digital learning platforms. Second, it offers empirical feasibility evidence from a higher education context undergoing digital transformation, demonstrating the practical viability of combining instructional design frameworks with AI-driven recommendation systems and learning analytics.

The originality of this study should therefore be understood not as the introduction of individual technologies such as ADDIE, learning analytics, or AI recommendations, but as their systematic operationalization within a unified pedagogically driven platform architecture. The integration of semantic concept extraction, knowledge graph construction, learning analytics, and instructional design provides an adaptive recommendation mechanism that extends beyond the functionality typically available in conventional LMS platforms.

Despite these contributions, several limitations must be acknowledged. The study was conducted within a single institutional context with a relatively small participant sample, limiting the generalizability of the findings. In addition, as a feasibility study, it does not evaluate the platform's direct impact on learning outcomes. Future research
should prioritize outcome-based evaluation through quasi-experimental designs that measure pre-and post-learning performance, retention rates, and platform

engagement analytics across experimental and control groups. Multi-institutional, longitudinal studies will be essential for establishing the generalizability of the platform's educational effectiveness across diverse higher education contexts. Further refinement of the AI recommendation module, enhancement of cross-device compatibility, improvement of interface label clarity, and strengthening of onboarding and independent task completion support will be critical for improving the platform's scalability, accessibility, and user adoption across diverse higher education environments.

Future research will combine perception-based feasibility evaluation with objective learning analytics, task-based usability measures, and learning outcome indicators to provide stronger empirical evidence of the platform's educational effectiveness.

Overall, the findings indicate that the IDLP represents a viable, pedagogically grounded solution for supporting integrative blended instruction and provides a strong foundation for future research and development in intelligent digital learning systems.

CONFLICT OF INTEREST

The authors declare that they have no conflict of interest.

AUTHOR CONTRIBUTIONS

Shokhista Allamova: Conceptualization, methodology, software, formal analysis, investigation, data curation, writing—original draft preparation, visualization, and project administration. Sanobar Rizayeva: Supervision, writing—review and editing, validation. Saodaddin Rasulov: Supervision, methodology, writing—review and editing. Saginbay Urinbaev: Resources, writing—review and editing. Khurshida Kadirova: Validation, writing—review and editing. Shakhrizod Ganieva: Software, visualization, writing—review and editing. All authors had approved the final version.

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REFERENCES

[1] L. M. C. Benavides, J. C. A. Tamayo, L. Arenas-Arenas, and D. E. Torres-Madroñero, "Digital transformation in higher education institutions: A systematic literature review," *Sensors*, vol. 20, no. 11, 3291, 2020.

[2] A. Haleem, M. Javaid, M. A. Qadri, and R. Suman, "Understanding the role of digital technologies in education: A review," *Sustainable Operations and Computers*, vol. 3, pp. 275–285, 2022.

[3] H. H. Jacobs, *Interdisciplinary Curriculum: Design and Implementation*, Alexandria, VA: Association for Supervision and Curriculum Development, 1989.

[4] S. M. Drake and J. L. Reid, "Integrated curriculum as an effective way to teach 21st century capabilities," *Asia Pacific Journal of Educational Research*, pp. 31–50, 2018.

[5] D. R. Garrison and H. Kanuka, "Blended learning: Uncovering its transformative potential in higher education," *Internet and Higher Education*, vol. 7, no. 2, pp. 95–105, 2004.

[6] T. Bates, *Teaching in a Digital Age*, 2nd ed. Vancouver, BC: Tony Bates Associates Ltd., 2019.

[7] N. Alseelawi, H. T. Hazim, H. Z. Alrikabi, K. Aljanabi, and H. Abed, "Design and implementation of an e-learning platform using ADDIE instructional model," *International Journal of Interactive Mobile Technologies*, vol. 14, no. 11, pp. 34–51, 2020.

[8] S. Timotheou, O. Miliou, Y. Dimitriadis, S. V. Sobrino, N. Giannoutsou, R. Cachia, A. Monés, and A. Ioannou, "Impacts of digital technologies on education and factors influencing schools' digital capacity and transformation," *Education and Information Technologies*, vol. 28, pp. 6695–6726, 2023.

[9] B. Bray and K. McClaskey, *Make Learning Personal: The What, Who, WOW, Where, and Why*, Thousand Oaks, CA: Corwin Press, 2013.

[10] J. Mella-Norambuena, A. Chiappe, and M. G. Badilla-Quintana, "Theoretical and empirical models underlying the teaching use of LMS platforms in higher education: A systematic review," *Journal of Computers in Education*, vol. 12, pp. 997–1023, 2025

[11] T. Gkrimpizi, V. Peristeras, and I. Magnisalis, "Defining the meaning and scope of digital transformation in higher education institutions," *Administrative Sciences*, vol. 14, no. 3, 48, 2024.

[12] R. M. Branch, *Instructional Design: The ADDIE Approach*, New York, NY: Springer, 2009.

[13] B. H. Khan, "People, process and product continuum in e-learning: The e-learning P3 model," *Educational Technology*, vol. 44, no. 5, pp. 33–40, 2004.

[14] J. W. Ross, C. M. Beath, and M. Mocker, *Designed for Digital: How to Architect Your Business for Sustained Success*, Cambridge, MA: MIT Press, 2019.

[15] S. Zizikova, P. Nikolaev, and A. Levchenko, "Digital transformation in education," in *Proc. E3S Web of Conferences*, EDP Sciences, 2023, vol. 381, 02036.

[16] P. Brusilovsky, "Adaptive hypermedia," *User Modeling and User-Adapted Interaction*, vol. 11, no. 1–2, pp. 87–110, 2001.

[17] G. Siemens and P. Long, "Penetrating the fog: Analytics in learning and education," *EDUCAUSE Review*, vol. 46, no. 5, pp. 30–32, 2011.

[18] I. Roll and R. Wylie, "Evolution and revolution in artificial intelligence in education," *International Journal of Artificial Intelligence in Education*, vol. 26, no. 2, pp. 582–599, 2016.

[19] C. Wang, X. Li, and Y. Zhang, "Education reform and change driven by digital technology: A bibliometric study from 2000 to 2022," *Humanities and Social Sciences Communications*, vol. 11, 256, 2024.

[20] M. R. Fayziyeva, "Methodology for Developing and Implementing an Educational Platform in the Context of Digital Transformation," PhD. dissertation, Chirchiq State Pedagogical University, Chirchiq, Uzbekistan, 2023. (in Uzbek).

[21] S. Newman, *Building Microservices: Designing Fine-Grained Systems*, CA: O'Reilly Media, 2015.

[22] C. Pahl and P. Jamshidi, "Microservices: A systematic mapping study," in *Proc. 6th International Conference on Cloud Computing and Services Science (CLOSER)*, Rome, Italy, 2016, pp. 137–146.

[23] R. Su and X. Li, "Modular monolith: Is this the trend in software architecture?" in *Proc. 1st International Workshop on New Trends in Software Architecture*, ACM, 2024, pp. 10–13.

[24] H. Gu, Q. Zhang, and Y. Liu, "Research on online teaching platform system based on microservice architecture," in *Proc. MATEC Web of Conferences*, EDP Sciences, 2022, vol. 355, 03058.

[25] C. Pautasso, O. Zimmermann, M. Amundsen, J. Lewis, and N. Josuttis, "Microservices in practice, part 1: Reality check and service design," *IEEE Software*, vol. 34, no. 1, pp. 91–98, Jan. 2017.

[26] R. Golande, P. Kokate, A. Jangle, V. Ghadge, A. Thorat, and P. Yeole, "Student management system with admin, teacher, and student roles," *Alochana Journal*, vol. 14, no. 5, pp. 580–587, 2025

[27] X. Ren, H. Wang, and T. Cai, "Design and implementation of a microservices-based online learning platform," in *Proc. 7th International Conference on Educational Technology, Computer and Internet (EITCE 2023)*, Atlantis Press, 2023, pp. 455–460.

[28] D. Salunke, S. Patil, and A. Shinde, "A survey paper on role based access control," *International Journal of Advanced Research in Computer and Communication Engineering*, vol. 2, no. 3, pp. 1340–1345, Mar. 2013.

[29] M. Jones, J. Bradley, and N. Sakimura. (May 2015). JSON Web Token (JWT). RFC 7519. Internet Engineering Task Force. [Online]. Available: https://tools.ietf.org/html/rfc7519

[30] E. F. Codd, "A relational model of data for large shared data banks," *Communications of the ACM*, vol. 13, no. 6, pp. 377–387, Jun. 1970.

[31] A. Silberschatz, H. F. Korth, and S. Sudarshan, *Database System Concepts*, 7th ed. New York, NY: McGraw-Hill Education, 2020.

[32] L. Morshchinina, A. Petrov, and I. Semenov, "A comparative study of web frontend reactivity frameworks for educational applications," in *Proc. Fourth International Conference on Optics, Computer Applications, and Materials Science (CMSD-IV 2024)*, 2025, pp. 187–198.
[33] T. A. Nguyen, "A comparative analysis of Webpack and Vite as JavaScript build tools for modern web development," B.S. thesis, Dept. Information Technology, Metropolia University of Applied Sciences, Helsinki, Finland, 2024.
[34] J. Preece, Y. Rogers, and H. Sharp, *Interaction Design: Beyond Human-Computer Interaction*, 5th ed. Chichester, UK: John Wiley & Sons, 2019.
[35] J. A. S. Cenita and Z. R. de Guzman, "Education in the digital world: From the lens of millennial learners," *International Journal of Computing Sciences Research*, vol. 7, pp. 1816–1829, 2023.
[36] D. George and P. Mallery, *IBM SPSS Statistics 26 Step by Step: A Simple Guide and Reference*, 17th ed. New York, NY: Routledge, 2019.

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