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AI-supported pedagogical pipeline for computing students' research competence

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ABSTRACT

This study evaluates an artificial intelligence (AI)-enabled co-curricular student club model implemented at two regional universities, organized as a staged four-part pipeline comprising competitive programming, hackathon prototyping, startup/project development, and final project defense. A matched pre/post design was used to assess changes in students' objective computing knowledge, measured through a supervised computing skills test, and self-reported constructs, measured through an AI literacy and learning disposition survey. Outputs from club activities were also documented and combined into an OutputsIndex. The analyses showed statistically significant improvements in both computing knowledge and survey-based constructs, indicating that the intervention strengthened both foundational technical competence and students' readiness for applied, performance-based work. AI literacy was also significantly associated with both knowledge scores and real-life outcomes, even after controlling for site and baseline differences, indicating that students with stronger AI-related competencies applied their learning more effectively to performance-based outputs. The findings support the potential of scalable, evidence-based IT student pipelines in Kazakhstan's higher education context, and suggest that structured, AI-supported pathways can align skill development with responsible AI use, stronger learning outcomes, and measurable real-world performance.

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1. INTRODUCTION

Universities in Kazakhstan, particularly regional universities, face two related tasks: strengthening the algorithmic, programming, and software engineering skills that support employability, and helping students translate these skills into portfolio-ready outputs such as contests, hackathons, startup projects, and research products. Achieving this goal requires more than additional programming practice, because students also need opportunities to work under time pressure, uncertainty, external evaluation, and public demonstration. This challenge has become more complex as generative artificial intelligence (GenAI) tools increasingly influence how code is created, tested, debugged, documented, and communicated [1].

Structured, activity-based learning has been shown to improve engagement and measurable outcomes when digital tools are aligned with learning tasks rather than added superficially [2]–[5]. This aligns with research showing that smart technologies should be integrated through instructional design, not treated as technical add-ons [6]. In computing education, this alignment is especially important because students need repeated practice, feedback, and authentic production opportunities. Therefore, the present study treats programming practice, project work, and AI-supported learning as connected stages rather than separate interventions.

Competitive programming is an important part of this literature because it gives students repeated opportunities to develop algorithmic thinking, debugging skills, problem-solving discipline, and performance under time constraints [7]. Studies on competitive programming, gamified learning, and AI-driven innovation suggest that these formats can improve mastery and motivation when they are organized around clear learning principles and regular feedback [8]. Platform-based approaches further support this process through online judges, analytics, contest modes, and remote coding environments that make learner progress more visible [9]. However, competitive programming alone does not show whether students can transform algorithmic competence into collaborative products, research outputs, or startup-oriented solutions.

Hackathon-style and project-based learning provide a complementary direction by moving students from individual problem solving to team-based production under realistic constraints. Educational hackathons support teamwork, creativity, practical problem solving, and rapid prototyping, especially when students must produce visible outputs within limited timeframes [10]. Project-based learning also supports cognitive, practical, and affective outcomes through authentic production and applied problem solving [11]. In Kazakhstan, technology-rich and practice-oriented educational environments also show that engagement in authentic tasks and artifacts can be linked to improved learning outcomes and applied competence [12]. Nevertheless, hackathons and project-based formats are often implemented as separate events, and the longer developmental connection between programming practice, product development, research competence, and startup readiness remains insufficiently evaluated.

The widespread availability of GenAI tools has also changed how effective training for IT students should be designed. Students can use AI tools for conceptual clarification, debugging, code drafting, documentation, ideation, and iterative improvement, but they also face risks related to inaccurate outputs, dependence on AI, academic integrity, and reduced ownership of solutions [13]–[15]. Research on AI-assisted instruction therefore suggests that educational programs should include verification guidelines, disclosure practices, and integrity safeguards instead of assuming that access to AI tools automatically produces learning [16]. This is especially important in programming contexts, where GenAI can disrupt assignments and competitions, and where traditional plagiarism detection may be insufficient for identifying inappropriate or unverified AI-supported work [17], [18].

Broader higher education research also emphasizes the need to connect AI use with assessment, governance, and measurable competence development. Systematic reviews report benefits such as faster feedback, personalization, efficiency, and assessment support, while also identifying risks related to privacy, bias, transparency, fairness, and integrity [19]–[21]. Quasi-experimental and AI-integrated learning pathway studies suggest that students can improve performance, engagement, and learning efficiency when AI tools are embedded in structured learning environments with dynamic assessment and adaptive support [22], [23]. Responsible AI use also depends on digital literacy, ethical awareness, and students' ability to evaluate AI-generated outputs critically [24]. Framework-based work, including the AI-TEACH model, similarly argues that AI should be integrated pedagogically and ethically rather than treated only as a technical productivity tool [25].

Despite this growing evidence, several gaps remain. Existing studies show that competitive programming, hackathon-style experiential learning, entrepreneurship education, research training, and AI can support the development of computing students, but these components are usually examined separately. Limited empirical evidence exists on end-to-end, AI-supported talent pipelines that connect these components through common outcome measures across multiple universities. This gap is especially important for regional higher education institutions, where students may need structured routes from basic skill acquisition to portfolio-ready outcomes and responsible participation in AI-mediated digital work.

The novelty of this study lies in evaluating an end-to-end, AI-supported pedagogical pipeline that connects competitive programming, hackathon prototyping, startup and research development, and project defense within one measurable co-curricular model for regional university IT students. As shown in Figure 1, the pipeline is significant for educational practice because it gives universities a repeatable model for moving students from foundational programming practice to externally visible outputs. It is relevant for policy because it offers a scalable co-curricular mechanism for AI-ready workforce development, and it has societal value because it supports regional students in building innovation, research, employability, and responsible AI skills. The study is guided by four research questions.

– How do students' key competencies change from pre-test to post-test, including competitive programming self-efficacy, AI literacy and responsible use, research competence, startup readiness, teamwork and project execution, and motivation and commitment?
– How much do students improve on their programming and algorithmic knowledge scores from pre-test to post-test?
– How do post-test outcomes, including objective knowledge and practical achievements, relate to students' AI literacy, teamwork, and motivation?
– Are there statistically significant differences in baseline levels or pre-test/post-test changes between the two participating universities?

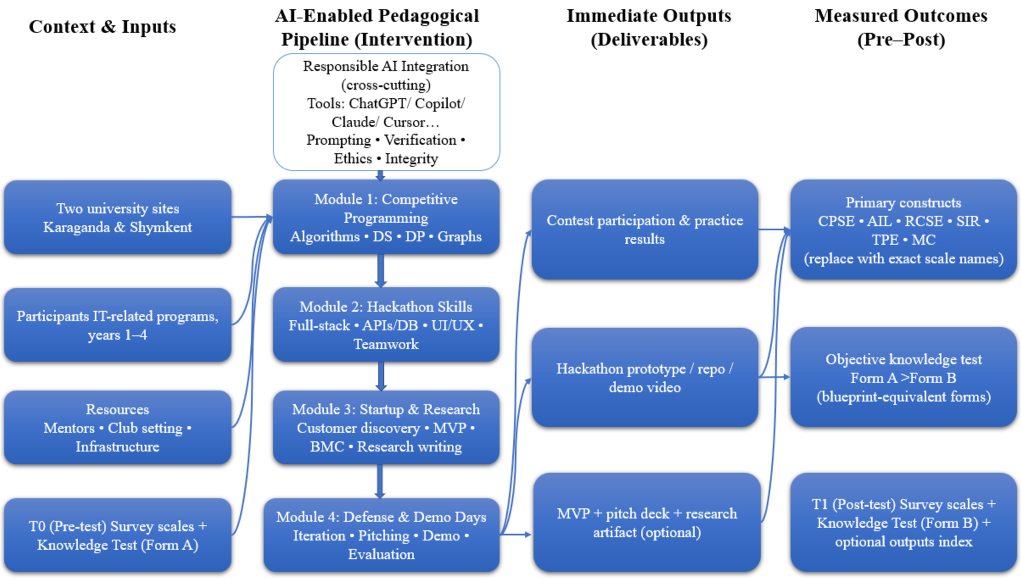

Figure 1. Conceptual framework of the AI-enabled pedagogical pipeline

2. PROGRAM DESCRIPTION (INTERVENTION)

2.1. Program title and setting

The intervention was delivered through the predefined student club program "IT Research Lab: From Research to Startups". The intervention took place at two university sites in Kazakhstan where student scientific clubs already existed to support competitive activities and project-based innovation; the characteristics of the two sites are summarized in Table 1. The intervention was offered as a sequential curriculum at both sites, with the same order of modules and two identical points of measurement (T0 and T1).

Table 1. Study sites and programs

Site	University	Student club	Degree programs involved
Site 1	Karaganda National Research University named after Academician E.A. Buketov	IT Research Lab	6B06103 Information Systems; 6B06105 Software Engineering; 6B01505 Informatics
Site 2	Shymkent University	IT and AI Innovators Club	6B01502 Informatics; 6B01506 Physics–Informatics; 6B06101 Computer Engineering and Software

2.2. Curriculum structure (4 modules)

The intervention consisted of 128 contact hours organized into four sequential modules. The modules were designed to move students from individual algorithmic practice to team-based product development, startup and research preparation, and final project defense. Each module included hands-on activities, mentor feedback, and applied outputs connected to the overall pipeline.

– Module 1: competitive programming (32 hours)

Students learned core problem-solving fundamentals through algorithms, including sorting and searching, two pointers and sliding window techniques, basic data structures, greedy methods, dynamic programming, and graph algorithms such as DFS, BFS, shortest paths, and minimum spanning trees.

Students practiced these topics through structured task sets and virtual competitions. This module aimed to strengthen algorithmic confidence, debugging discipline, and problem solving under time constraints.

– Module 2: hackathon skills (36 hours)

Students learned to complete the product development process under a time constraint. They were exposed to idea generation and prototyping, building a full stack application (e.g., React and either Node.js/Python) with APIs and databases, deploying applications, UI/UX for demo-ready products, pitching their completed projects, as well as workflow through the use of Git, code reviews, and task tracking using tools such as Jira. The module connected technical implementation with teamwork, presentation, and delivery of a functional prototype.

– Module 3: startup and research (32 hours)

The focus was on discovering and validating a problem (Lean Startup Methodology, customer development, conducting interviews), defining an MVP and iterating through the process of validating a solution for the problem. Students also worked on business-model development and research-oriented communication. This module prepared students to transform project ideas into pitch, startup, or research artifacts.

– Module 4: project defense and demo days (28 hours)

This module emphasized final project refinement, presentation, and public demonstration. Students received mentoring to prepare their projects for competitions, hackathons, or institutional demo-day events. The module concluded with final project demonstrations and defenses, where students explained their technical decisions and outputs.

2.3. Implementation format

The intervention was implemented as a structured club-based learning experience that combined facilitated instruction, guided practice, mentoring, team project work, and public demonstration. The main delivery formats included regular meetings, individual and team mentoring, prototype-to-demo project development, an internal milestone hackathon after Module 2, and a culminating demo day/project defense after Module 4. This format allowed students to practice technical skills, receive feedback, revise their work, and produce visible outputs across the program.

Responsible and effective use of AI tools was integrated across all modules. Students used tools such as ChatGPT, GitHub Copilot, Claude, Cursor, and related productivity or design tools for conceptual clarification, debugging, code drafting, ideation, documentation, and iterative improvement. However, AI use was accompanied by verification expectations, academic-integrity rules, explanation of AI-assisted solutions, and student responsibility for final decisions and outputs. In this way, AI was treated as a learning and productivity support, not as a replacement for students' reasoning, authorship, or project ownership. The structure and timeline of the program are presented in Figure 2. The figure shows the sequence of modules, the contact hours for each module, the placement of major milestones such as the internal hackathon and final demo day, and the two measurement points: T0, which included the pre-survey and knowledge test Form A, and T1, which included the post-survey and knowledge test Form B.

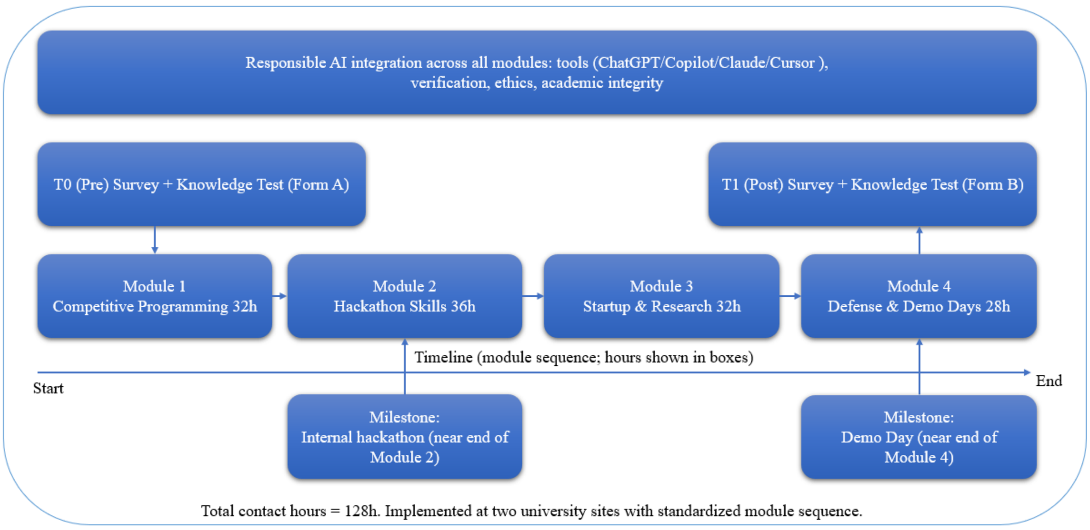

Figure 2. Program structure and timeline of "IT Research Lab: From Research to Startups"

3. METHOD
3.1. Study design
This study used a two-site quasi-experimental pre-test/post-test design to evaluate the effectiveness of the AI-supported student club program. Data collection occurred at T0 (pre-test), immediately prior to the commencement of program activities, and at T1 (post-test), following completion of all program activities. The primary unit of analysis was the individual student, and pre-test and post-test responses were linked via an anonymous participant code so that matched (within-subject) comparisons could be made.

3.2. Setting and program context
The study was conducted at two universities in Kazakhstan with existing IT-oriented student clubs. The same four-module club program was implemented at both sites, following the same module order and measurement structure.

3.3. Participants and sampling
Undergraduate students from Years 1–4 enrolled in information technology (IT) programs at the two universities participated in the study. Participants were either currently involved in a student club or newly joined during the data collection period. To take part, participants had to meet three criteria: be an undergraduate student; be enrolled in an IT-related program; and have provided informed voluntary consent to participate. Participation was optional, and students' grades or academic standing were not affected by participation or non-participation. Table 2 provides overall site/timepoint sample distributions by site and timepoint, including year of study at T0. Figure 3 shows participant flow from T0 to T1, including the matched analytic sample overall and by site, as well as unmatched or unavailable cases.

Table 2. Participant distribution by site, timepoint, and year of study

Category	Group	N
T0 (pre-test) by site	Karaganda	83
	Shymkent	65
	Total T0	148
T1 (post-test) by site	Karaganda	76
	Shymkent	57
	Total T1	133
Matched T0–T1 analytic sample	Karaganda	71
	Shymkent	53
	Total matched	124
T0 (pre-test) by year of study	Year 1	39
	Year 2	44
	Year 3	37
	Year 4	28
	Total T0	148

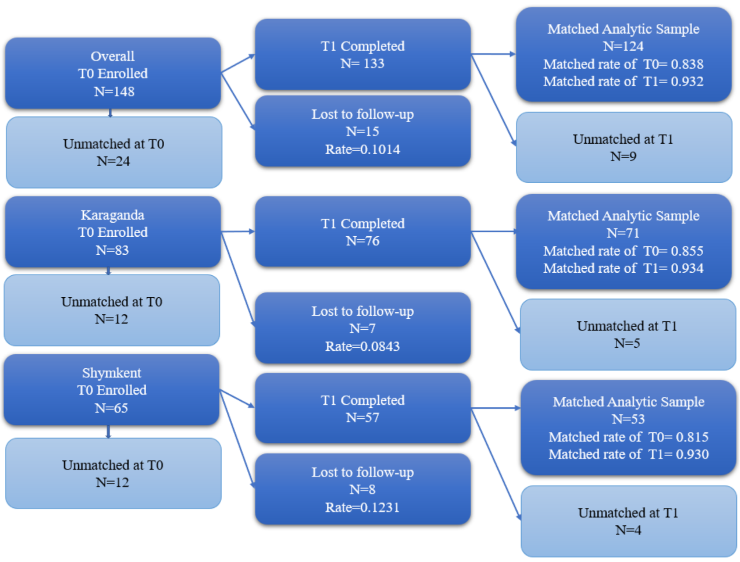

Figure 3. Participant flow and matched analytic sample by site

3.4. Procedure and data collection

The research team implemented a standardized data collection protocol at both sites. First, students received information about the student club program and the purpose of the study, after which informed consent was obtained electronically. Second, each participant created a self-generated anonymous code based on the same general instructions, allowing the research team to match T0 and T1 responses without collecting personally identifiable information. Third, at T0, participants completed a structured survey and an objective knowledge mini-test, Form A, which assessed foundational programming and algorithmic concepts related to the program content.

After the pre-test stage, students participated in the four-module club curriculum. At T1, participants completed the same structured survey for pre/post comparison and a parallel objective knowledge mini-test, Form B. Form B followed the same content blueprint and difficulty targets as Form A, but used different questions to reduce memorization effects.

Both survey administrations were conducted online, while the knowledge mini-tests were administered under supervised face-to-face conditions. The mini-tests followed identical instructions at both sites and had a predetermined time limit of approximately 24 minutes. During the knowledge test, students were not allowed to use textbooks, GenAI tools, or other external sources. These identical assessment conditions supported implementation fidelity across the two sites.

3.5. Measures and instruments

To make the intervention-to-measurement logic explicit, Table 3 summarizes how each program module was intended to support specific competency domains and how those domains were operationalized in the study. Because the intervention was designed as a staged pipeline rather than as a set of isolated activities, some competencies were primarily targeted within a single module, whereas others—particularly AI literacy, motivation, and applied output production—were developed across multiple modules. This alignment guided the interpretation of pre-test/post-test changes and post-test outcome indicators in relation to the structure of the program.

Table 3. Alignment of program modules, targeted competencies, and study measures

Module	Main instructional focus	Primary competencies targeted	Related study construct(s)/ indicator(s)	Main evidence collected
Module 1. Competitive programming (32 hours)	Algorithmic problem solving, data structures, debugging, solving tasks under time constraints, virtual contests	Algorithmic thinking, programming confidence, foundational computing knowledge, disciplined problem solving	Competitive programming self-efficacy (CPSE); Objective knowledge mini-test	Pre/post survey (CPSE); Form A/Form B knowledge scores
Module 2. Hackathon skills (36 hours)	Team-based prototyping, rapid product development, version control, UI/UX, pitching, deployment workflows	Team collaboration, project execution, practical problem solving, product-oriented development	Teamwork and project execution (TPE); contribution to OutputsIndex_T1	Pre/post survey (TPE); hackathon participation; prototype/repository/demo outputs
Module 3. Startup and research (32 hours)	Problem identification, customer discovery, MVP scoping, research framing, pitch preparation, business model development	Research competence, innovation readiness, problem framing, early entrepreneurial thinking	Research competence self-efficacy (RCSE); Startup and innovation readiness (SIR); contribution to OutputsIndex_T1	Pre/post survey (RCSE, SIR); pitch decks, abstracts, prototype and startup-related artifacts
Module 4. Project defense and demo days (28 hours)	Final project refinement, presentation, defense of decisions, demonstration of outputs, mentor feedback	Communication of results, ownership of solutions, applied performance, accountability, integration of prior learning	Contribution to RCSE, SIR, TPE, MC; contribution to OutputsIndex_T1	Demo/presentation artifacts, deployment/demo evidence, mentor-documented outputs
Responsible AI integration (cross-cutting across all modules)	Use of ChatGPT, GitHub Copilot, Claude, Cursor, and other tools for ideation, debugging, drafting, and refinement with verification and integrity checks	AI literacy, responsible AI use, verification habits, ethical awareness, assisted productivity with retained ownership	AI literacy and responsible use (AIL)	Pre/post survey (AIL); observed AI-supported workflow expectations embedded across activities
Whole-program effect	Sequential progression from individual problem solving to collaborative development and public presentation	Motivation, persistence, commitment to sustained participation across the pipeline	Motivation and commitment (MC); OutputsIndex_T1	Pre/post survey (MC); participation indicators and end-of-program outputs

3.5.1. Survey constructs (Likert-type scales)

The pre-test and post-test surveys had the same structure and included six multi-item constructs measured on a 7-point Likert scale, where 1 indicated "strongly disagree" and 7 indicated "strongly agree." Composite scores were calculated by averaging the items within each construct. The six constructs were competitive programming self-efficacy (CPSE), AI literacy and responsible use (AIL), research competence self-efficacy (RCSE), startup and innovation readiness (SIR), teamwork and project execution (TPE), and motivation and commitment (MC).

CPSE measured students' perceived ability to develop solutions, apply core programming strategies, and participate in competitive programming. AIL measured students' ability to use AI tools effectively while verifying outputs, understanding limitations, and following academic-integrity principles. RCSE measured confidence in developing research questions, using literature, designing studies, and communicating research results. SIR measured readiness to identify problems, validate hypotheses, create minimum viable products, and pitch solutions. TPE measured competence in collaborative workflows, including GitHub use, task management, communication, and project delivery under constraints. MC measured students' motivation, persistence, and commitment to competitive programming, project work, research, and startup-related activity. The survey also collected limited background information, including year of study, prior programming experience, primary programming languages, and platform exposure.

3.5.2. Objective knowledge mini-test (Form A/Form B)

An objective knowledge mini-test was used to measure students' learning gains in foundational programming and algorithmic concepts. Form A was administered at T0, and Form B was administered at T1. Both forms contained 12 questions covering algorithmic reasoning, complexity, core data structures, standard programming methods, debugging, and conceptual distinctions. The two forms included both multiple-choice and open-ended items. Students received one point for each correct answer, and the total score was calculated by summing the number of correct responses. Form B used different questions from Form A to reduce memorization effects, but both forms followed the same content blueprint, answer-key structure, and difficulty targets.

3.5.3. Participation and outcome indicators (post-test)

The post-test also collected evidence of students' applied engagement and practical outputs during the intervention. These indicators included the number of programming problems solved, the number of contests attended, hackathon participation coded as 0=No and 1=Yes, and the number of distinct artifact types completed by the end of the program. Artifact types included demo or presentation materials, pitch decks, prototype or repository evidence, and deployment evidence. These four indicators were combined into an aggregate variable named OutputsIndex_T1, which represented applied engagement and output production. To place the indicators on a common scale, the number of problems solved was capped at 200 and divided by 200, the number of contests was capped at 10 and divided by 10, hackathon participation was treated as a binary value, and the number of artifact types was divided by 4. The arithmetic mean of these four scaled indicators was then converted to a 0–10 scale, where higher values represented greater applied engagement and output production. Because OutputsIndex_T1 combined different output-related indicators rather than internally consistent survey items, internal consistency reliability was not used as an evaluation criterion for this index. Where available, self-reported outcome data were checked against mentor records, demo-day materials, and repository links.

3.6. Reliability and measurement quality

Internal consistency of the multi-item constructs was evaluated separately at T0 and T1 using Cronbach's alpha and, where appropriate, McDonald's omega. Reliability was calculated at both time points to check whether the constructs remained stable across measurements. Composite scores were created according to the completeness rule. For the knowledge mini-test, item-level response patterns were reviewed to identify questions that were overly easy, overly difficult, or unclear.

3.7. Data preparation and quality rules

Survey data exported from the online platform were processed using consistent data-preparation rules. T0 and T1 responses were matched using anonymous participant codes. Responses with missing, invalid, or non-matchable codes were treated as unmatched and were not included in the matched pre/post analytic sample. Duplicate participant codes were reviewed before analysis. When duplicate matched records were identified, the most complete matched response record was retained, and inconsistent or incomplete duplicate records were removed. Composite construct scores were created only when at least 82% of the items for the relevant construct were completed, which helped maintain measurement stability while minimizing unnecessary case exclusion. Knowledge-test responses were scored using predefined answer keys for multiple-choice items and scoring rubrics for short-answer items. The final analytic sample consisted of 124 students with matched T0 and T1 records, allowing within-subject pre/post comparisons. Unmatched responses were retained only for descriptive purposes when appropriate.

3.8. Statistical analysis

The analysis followed four main steps. First, descriptive statistics were used to summarize baseline characteristics overall and by university site, including year of study, programming experience, and platform exposure. Second, reliability analyses were conducted for each multi-item construct at T0 and T1 using Cronbach's alpha and McDonald's omega. Third, pre/post changes were examined using paired-sample comparisons for all survey constructs, including CPSE, AIL, RCSE, SIR, TPE, and MC. Matched comparisons between Form A at T0 and Form B at T1 were also conducted to assess objective knowledge gains. Effect sizes, including paired Cohen's d with confidence intervals, were reported to estimate the magnitude of change and to support practical interpretation of the results. Fourth, site comparisons and association analyses were conducted. Baseline levels and change scores were compared between the two universities. Associations between post-test outcomes, including knowledge scores and participation/output indicators, and key predictors, especially AI literacy, teamwork, and motivation, were examined using correlation and multiple regression models. Adjusted regression models included site, year of study, and prior programming experience as covariates; baseline values were included when a true baseline measure was available. Conventional significance testing was applied using $p<.05$, but interpretation emphasized effect sizes, confidence intervals, and practical significance alongside statistical significance.

3.9. Ethical considerations

The Ethics Committee of Karaganda National Research University, named after Academician E.A. Buketov, reviewed and approved the study protocol (protocol #10) on September 1, 2025. Both universities followed the approved protocol, instrument(s), and informed consent process identically. Shymkent University granted institutional permission to conduct data collection under the approved protocol/consent. Participants in this study were informed that their participation was wholly voluntary. Informed consent was obtained from each student. Data provided by responding participants were anonymously coded by a self-generated matching code, which enabled linkage between individual pre/post measures. Data were securely stored, and only aggregate analysis results are reported.

4. RESULTS

4.1. Participant flow and analytic sample

Overall, the level of attrition among those participating in this study was moderate, with 15 students lost at post-test (10.1%). Since most of the participants remained engaged in the program, this high level of engagement suggests that this is a relatively common level of attrition for extracurricular activities. In addition to the fact that the matching only produced a final analytic sample (i.e., there were 124 students who had both T0 and T1 record), the high level of matching indicates that, for the vast majority of T1 respondents, their matched record with T0 indicates a true change rather than the result of mismatched identities. Matching percentage was also considerably high for both T0 (83.8%) and T1 (93.2%), indicating that the vast majority of T1 respondents could be matched back to their T0 records, thus decreasing the chances of the results being due to carelessness on the behalf of those with mismatched identities.

When examining patterns of retention among the two different sites (i.e., Karaganda and Shymkent), there is only a slightly greater retention level at Karaganda (8.4% attrition) compared to Shymkent (12.3% attrition). While this difference in attrition percentages is very small, it may lead to somewhat of an underrepresentation of the less consistent or engaged students at the Shymkent site. Nevertheless, the matching percentages are similar (≈93%) for both sites, which indicates that the samples produced at each site were fairly consistent. The breakdown of enrolled, retained, matched, and unmatched students is depicted in Figure 3.

4.2. Reliability and descriptive summary

Table 4 summarizes reliability estimates (α/ω between T0 and T1) for all constructs measured. The survey measures showed satisfactory internal consistency at both time points, with most constructs exhibiting stable or slightly improved reliability at T1 as a result of participants gaining a clearer conceptualization of the constructs following structured training (i.e., responses becoming more coherent). The importance of these reliability findings is practical because they provide justification for treating each construct as one composite score (i.e., mean of the items comprising that construct) and for taking pre-post differences as significant change rather than simply measurement error. The fact that AIL had such consistently high reliability is critical given the key role it plays in subsequent association models (AIL→outcomes), as the high internal consistency will reduce attenuation of the relationship between AIL and its associated outcomes, thereby increasing our confidence in the relationships being observed.

Table 4. Measures and reliability of the study instruments

Measure/Construct	Items	Reliability T0 (α/ω)	Reliability T1 (α/ω)
Competitive programming self-efficacy	8	0.84/0.86	0.87/0.88
AI literacy and responsible use	12	0.89/0.90	0.91/0.92
Research competence self-efficacy	10	0.86/0.87	0.88/0.89
Startup and innovation readiness	10	0.83/0.85	0.86/0.87
Teamwork and project execution	8	0.81/0.83	0.85/0.86
Motivation and commitment	8	0.79/0.81	0.82/0.84
Objective knowledge mini-test (Form A)	12	0.76/0.78	—
Objective knowledge mini-test (Form B)	12	—	0.74/0.76

4.3. Pre–post changes in survey constructs

All six survey constructs increased from T0 to T1. As shown in Figure 4, the direction of change was positive across both university sites. This pattern indicates that the program was associated with broad improvement across technical confidence, AI literacy, research competence, startup readiness, teamwork, and motivation. To start, AIL showed the most substantial upward shift (with a mean gain of 1.19 between pre-test and post-test, equivalent to 0.75 standard deviations), which is consistent with the program's focus on using GenAI for workflow optimization and on norms for responsible use, such as verification, testing, and documentation discipline. Accordingly, the largest gains were observed in AIL, which was the construct most directly targeted in the program design, rather than simply reflecting a general increase in confidence.

Next, TPE has also demonstrated sizeable growth and also supports the program logic (the additional work done on early C/C++ competition programming builds individual confidence in their ability to solve programming problems while working together in teams with a goal of completing a deliverable). However, RCSE and SIR have shown lower increases than the other constructs, which would be expected since the development of the research and entrepreneurial competencies will typically occur more slowly and usually require repeated iterations (writing, customer discovery, and pitching) before significant shifts in the level of achievement occur. Finally, the site level profiles also reflect this directional consistency (increased means across T1) in Karaganda by T1 compared to Shymkent, with Karaganda usually having slightly higher initial and/or final scores across all measures, as shown in Figure 4. These variations may be attributable to site level differences in preparation or implementation conditions, but regardless, the key finding is the overall direction of change indicating the degree of transferability of the program (pipeline) across different institutional contexts.

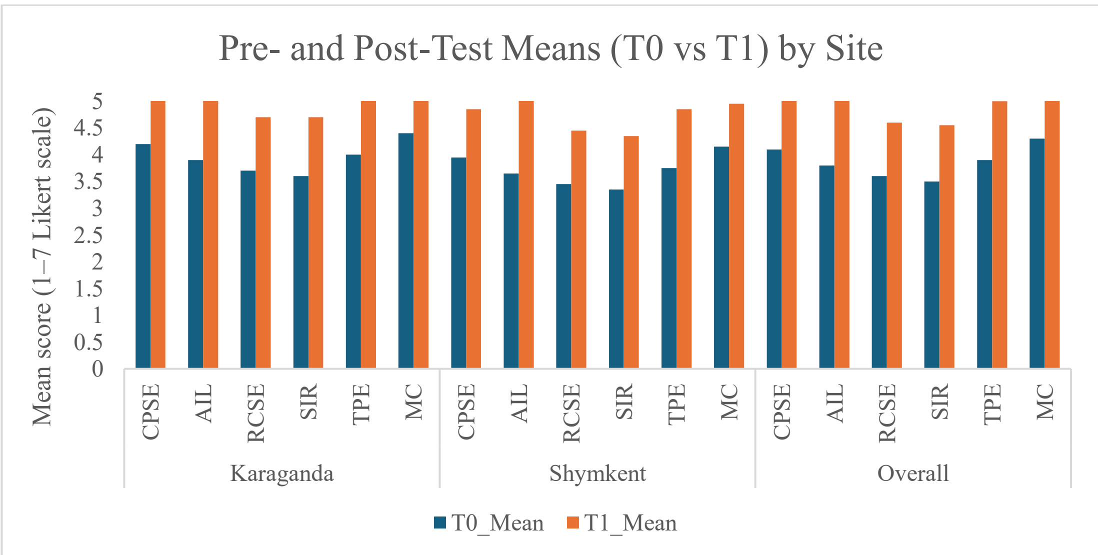

Figure 4. Pre–post changes in survey constructs (T0 vs T1) by site

4.4. Objective knowledge test results

Table 5 indicates that for the matched group, there was a statistically significant improvement of objective knowledge on the mini test (0-12) from pre-test to post-test mean score (pre: M=6.2, SD=2.1 vs post: M=7.6, SD=2.0); mean gain (Δ=1.4, 95% CI [1.06, 1.74]), paired d (d=0.74; p<.0001) indicating that the improvement was not limited to self-reported measures. Site-to-site comparisons (i.e., Shymkent and Karaganda) suggest that they demonstrated similar directions of change but with different magnitudes of change, as shown in Table 5. The difference in changes evidenced by the two sites demonstrated that Karaganda made a greater increase in their readiness level (6.5→8.1; Δ=1.6; 95% CI [1.17, 2.03]; d=0.89; p<0.001) than Shymkent did (5.8→6.9; Δ=1.1; 95% CI [0.55, 1.65]; d=0.55; p=0.001). When looking at these results with caution, this pattern of results may speak to baseline differences and/or differences in implementation quality (e.g., mentoring, engagement); however, both sites showed statistically significant improvement and substantial effect sizes supporting the conclusion that there were demonstrable gains in competency.

Table 5. Pre–post change in objective knowledge test scores

Site	Matched N	T0 Mean (SD)	T1 Mean (SD)	Δ Mean (95% CI)	Paired d	p-value
Overall	124	6.2 (2.1)	7.6 (2.0)	1.4 (1.06, 1.74)	0.74	<0.001
Karaganda	71	6.5 (2.0)	8.1 (1.9)	1.6 (1.17, 2.03)	0.89	<0.001
Shymkent	53	5.8 (2.2)	6.9 (2.1)	1.1 (0.55, 1.65)	0.55	<0.001

4.5. Relationship between AI literacy and outcomes

Multiple analyses confirmed a relationship between AI literacy measured by post-test (AIL_T1) and the corresponding outcome variables measured at the same time, as shown in Table 6. In the unanalyzed condition, the results produced both evidence of significant correlation (B=0.45, 95% C.I. (0.21,0.69); Std. β(0.35); p<001; R^2=0.10). Overall, results indicate that students evaluated as demonstrating high degrees of AI literacy and responsible use were, on average, scoring significantly higher than those who did not, implicating that using GenAI ultimately has the potential to enhance student learning, while also reinforcing the notion of verifying information before accepting it.

Table 6. Association between AI literacy at post-test (AIL_T1) and post-test outcomes

Outcome (Y)	Model	B (95% CI)	Std. β	p-value	R^2
KnowledgeTest_T1	Unadjusted	0.45 (0.21, 0.69)	0.35	<0.001	0.1
KnowledgeTest_T1	Adjusted	0.38 (0.12, 0.64)	0.29	0.004	0.2
OutputsIndex_T1	Unadjusted	0.60 (0.24, 0.96)	0.3	0.002	0.1
OutputsIndex_T1	Adjusted	0.52 (0.12, 0.92)	0.26	0.011	0.1

Note: Adjusted models control for site, year of study, and prior programming experience; baseline (T0) values were included when available. OutputsIndex_T1 is a 0–10 composite of applied outputs (solved problems, contest participation, hackathon participation, and artifact completion)

In the adjusted model, the association between AIL_T1 and knowledge outcomes was still statistically significant (B=0.38, 95% CI [0.12, 0.64]; Std. β=0.29; p=0.004; R^2=0.2), thus indicating that the association between AIL_T1 and knowledge outcomes continued to exist when accounting for the covariates considered. Similar associations were seen with applied outcomes as well. For OutputsIndex_T1, AIL_T1 exhibited a positive association in the unadjusted model (B=0.60, 95% CI [0.24, 0.96]; Std. β=0.30; p=0.002; R^2=0.1) and continued to be statistically significant in the adjusted model (B=0.52, 95% CI [0.12, 0.92]; Std. β=0.26; p=0.011; R^2=0.1). Therefore, both the objective knowledge measure and strong end-of-program Outputs/Achievements were reported by students with higher AI Literacy scores at post-test. In other words, the ability to accurately and responsibly use GenAI tools (prompting, debugging support, documentation, verification) appeared related to both learning and performance outcomes related to deliverables at the end of the pipeline. Adjusted models for both knowledge and applied outcome models were created using the sites where the students were studying (Karaganda vs Shymkent) and employing baseline covariates (i.e., year of study and prior programming experience) to account for initial differences.

4.6. Consolidated main outcomes table

Table 7 provides an overview of the program's overall impact on all core survey constructs and the knowledge test by displaying mean (SD) scores at both T0 and T1, as well as means and 95% CI for change, paired t test results as expressed by Cohen's d, and p-values both overall and by site. Within this summary table, two major trends emerge; first, that there are consistent positive changes in all constructs, and second, that there are significant improvements in objective knowledge, the degree of improvement being more substantial in Karaganda than in Shymkent, although significant improvement occurred at both sites.

Table 7. Main pre–post outcomes and effect sizes

Outcome	Site	N	T0 Mean (SD)	T1 Mean (SD)	Δ Mean (95% CI)	Paired d	p-value
CPSE	Overall	124	4.10 (1.05)	5.05 (0.95)	0.95 (0.79, 1.11)	1.06	<0.001
	Karaganda	71	4.20 (1.00)	5.20 (0.90)	1.00 (0.80, 1.20)	1.18	<0.001
	Shymkent	53	3.95 (1.10)	4.85 (1.00)	0.90 (0.64, 1.16)	0.95	<0.001
AIL	Overall	124	3.80 (1.10)	5.20 (0.90)	1.40 (1.23, 1.57)	1.47	<0.001
	Karaganda	71	3.90 (1.05)	5.30 (0.85)	1.40 (1.19, 1.61)	1.56	<0.001
	Shymkent	53	3.65 (1.15)	5.05 (0.95)	1.40 (1.12, 1.68)	1.4	<0.001
RCSE	Overall	124	3.60 (1.00)	4.60 (0.98)	1.00 (0.84, 1.16)	1.09	<0.001
	Karaganda	71	3.70 (0.98)	4.70 (0.95)	1.00 (0.79, 1.21)	1.14	<0.001
	Shymkent	53	3.45 (1.05)	4.45 (1.00)	1.00 (0.73, 1.27)	1.02	<0.001
SIR	Overall	124	3.50 (1.05)	4.55 (1.00)	1.05 (0.88, 1.22)	1.11	<0.001
	Karaganda	71	3.60 (1.02)	4.70 (0.98)	1.10 (0.88, 1.32)	1.2	<0.001
	Shymkent	53	3.35 (1.10)	4.35 (1.05)	1.00 (0.72, 1.28)	1	<0.001
TPE	Overall	124	3.90 (1.00)	5.00 (0.92)	1.10 (0.94, 1.26)	1.22	<0.001
	Karaganda	71	4.00 (0.95)	5.10 (0.88)	1.10 (0.90, 1.30)	1.29	<0.001
	Shymkent	53	3.75 (1.05)	4.85 (0.98)	1.10 (0.84, 1.36)	1.16	<0.001
MC	Overall	124	4.30 (0.95)	5.10 (0.90)	0.80 (0.64, 0.96)	0.91	<0.001
	Karaganda	71	4.40 (0.90)	5.20 (0.85)	0.80 (0.61, 0.99)	0.98	<0.001
	Shymkent	53	4.15 (1.00)	4.95 (0.95)	0.80 (0.55, 1.05)	0.89	<0.002
Knowledge test (0–12)	Overall	124	6.2 (2.1)	7.6 (2.0)	1.4 (1.06, 1.74)	0.74	<0.001
	Karaganda	71	6.5 (2.0)	8.1 (1.9)	1.6 (1.17, 2.03)	0.89	<0.001
	Shymkent	53	5.8 (2.2)	6.9 (2.1)	1.1 (0.55, 1.65)	0.55	<0.001

5. DISCUSSION

The evaluation of the "IT Research Lab: From Research to Startups" program at two universities in Kazakhstan showed that an end-to-end pipeline can support development across several domains through a defined sequence with measurable outcomes, including objective knowledge gains. A significant finding was that not only did participants' scores (test result) improve, but also the pattern of change coincided closely with the programmatic logic underlying the designed succession of activities. For example, AI literacy and responsible use showed the greatest increases; however, constructs related directly to delivery within constrained parameters, such as teamwork/project execution and confidence in competitive programming, also exhibited marked increases. Conversely, self-efficacy for research competence and readiness for start-up/innovation had moderate but significant increases. This areally-derived distribution aligns logically with theory, which indicates that a single cycle of structured contests and an internal hackathon creates confidence in using algorithms, execution discipline and tool-mediated work flow activities, while developing sustained competencies related to research design or innovation validation necessitates multiple iterations of structured events and a longer time frame for external feedback.

The results from the mini-test of objective knowledge further corroborated this interpretation by providing additional evidence of learning that was not based solely on self-reported evaluation. The knowledge gain observed on the objective test was moderate to large, with a relatively narrow confidence interval around the mean, indicating a consistent improvement in the matched analytic sample. This evidence is important because self-reported gains may reflect enthusiasm, a desire to respond positively, or changing perceptions of competence after instruction, whereas the objective test provides additional support that the program affected foundational knowledge as well as confidence-related outcomes. At the same time, the limited length and parallel-form structure of the test suggest that the scores should be interpreted as evidence of improvement in foundational knowledge rather than as a definitive measure of overall competence within the domain. This pattern is broadly consistent with prior work showing that practice-oriented programming instruction and digitally supported active learning can improve engagement, understanding, and measurable learning outcomes in computing-related education [2], [4]. Therefore, the overall results suggest that the pipeline supported both perceived competence and measurable learning outcomes.

The association models revealed another perspective on AI literacy as both an outcome of the intervention and a capability related to performance. In terms of post-test results, there was a higher level of AI literacy associated with a higher level of knowledge and an improved practical result based on the OutputsIndex, which was still true when adjusted models were used to analyze the data. These results suggest that using AI as a scaffold, together with verification routines, may help students use such tools more effectively for learning and applied production. Responsible AI literacy is important because it provides students with a way to use AI to enhance learning while also addressing institutional concerns about overdependence, deterioration of competence, and academic integrity. In this study, AI was not treated as a replacement for reasoning, but as a support that required students to verify, test, document, and explain their work. This interpretation is also compatible with recent research showing that AI-supported instruction can contribute to competence development and academic achievement, especially when technology use is embedded within clear pedagogical design rather than treated as an isolated tool [6], [16], [20].

Although the two sites were different, the results should be viewed through the lens of implementation heterogeneity, not as a case of superiority of one institution over another. Both universities demonstrated significant improvements on the knowledge test and across constructs, supporting the notion that the pipeline is transferable. However, Karaganda showed larger objective knowledge gains and a slightly higher retention rate than Shymkent, which may reflect more favorable implementation conditions, differences in mentoring intensity, more consistent attendance, or differences in baseline readiness. The current design does not allow these explanations to be separated, so the site differences should be interpreted as possible implementation effects rather than definitive institutional differences. This finding supports the need to measure fidelity indicators more explicitly in future implementation, including attendance, number of problems solved, repository activity, hackathon submissions, mentor feedback records, and structured assessment of AI verification routines.

6. EDUCATIONAL AND POLICY IMPLICATIONS

The practical implications are clear. Regional universities seeking replicable improvements may benefit from four design elements: a staged curriculum that moves from algorithmic problem solving to team-based project delivery, an internal hackathon with real deadlines, a final demonstration or defense format that requires students to explain and justify their work, and verification routines for the responsible use of AI tools. These elements are important because they connect technical training with applied output production and student accountability. Results indicate that the decision to allow for the use of AI is not critical; rather the critical decision is how the students use AI and if the use of AI is accompanied by expectations and methods of verification that allow the student to test, justify, and retain ownership of the solutions. Accordingly, AI literacy becomes a defined capability that supports learning and product development, rather than an uncontrolled confounding variable. In this way, responsible AI becomes part of the educational design rather than an uncontrolled external factor.

7. LIMITATIONS AND FUTURE RESEARCH

The findings should be interpreted with several limitations in mind. First, the quasi-experimental pre-test/post-test design did not include a randomized control group. Therefore, factors such as maturation, concurrent educational experiences, and selection effects may also have contributed to student improvement, limiting the ability to attribute all observed changes only to the intervention. Second, several constructs were measured through self-report, which may create response-shift bias. After completing the program, students may have adjusted their internal standards regarding their own competence. Although the objective knowledge mini-test strengthened the evaluation, its limited length and parallel-form structure mean that it should be interpreted as evidence of foundational knowledge gain rather than as a complete measure of overall competence.

The OutputsIndex also depends on its operational definition. Because some components were partly based on self-report, the index may reflect a combination of effort, opportunity, and reporting accuracy. Future studies should validate this index using external evidence, such as repository activity, mentor records, demo-day materials, contest records, and structured rubrics for student outputs. Another limitation concerns implementation fidelity. Although both sites followed the same program structure, the study did not fully measure differences in mentoring intensity, attendance, repository activity, hackathon submissions, or quality of project feedback. Future research should include stronger fidelity indicators to clarify which components of the pipeline contribute most strongly to student outcomes.

Future studies should use a matched comparison or waitlist-control design, a larger item bank for objective knowledge assessment, and longer-term follow-up. These improvements would help determine whether the pipeline produces durable outcomes beyond immediate post-test gains. Future research should also examine how responsible AI literacy relates to externally verifiable outcomes, including project quality, code ownership, AI verification practices, contest performance, internships, and continuing project development.

8. CONCLUSION

The study assessed a two-site club-level initiative, titled “IT Research Lab: From Research to Startups” in Kazakhstan, that progressed through staged delivery including competitive programming, hackathons, and startup/research activities, with cross-cutting principles of responsible AI used throughout the program. In a paired pre/post sample, participants showed a consistent increase in all measured constructs of competency, as well as a moderate to large increase on an objective knowledge test, providing evidence that the pipeline strengthened both perceived capability and measurable learning outcomes. At post-test, AI literacy was positively correlated with both objective knowledge and indicators of practical outcomes, which suggests that responsible AI competency is not merely an attitudinal outcome, but rather a meaningful facilitator of learning and production. The magnitude of the gains across the two sites was not equal, which may be attributable to varying implementation conditions and levels of readiness across cohorts; therefore, fidelity-focused replication is warranted. Overall, the findings support the feasibility and educational value of scalable, verification-driven, AI-enabled pipelines for developing research competence, computing competencies, and portfolio-ready outputs. The main contribution of the study is the demonstration that competitive programming, hackathon practice, startup and research work, and project defense can function as a coherent developmental pathway rather than as isolated activities. This model may also inform curriculum and co-curricular design in regional higher education contexts seeking stronger alignment between technical training, responsible AI use, and industry-relevant student outcomes. Future research should examine the long-term transferability of this model across other higher education institutions and under different implementation conditions.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization	I : **I**nvestigation	Vi : **Vi**sualization
M : **M**ethodology	R : **R**esources	Su : **Su**pervision
So : **So**ftware	D : **D**ata Curation	P : **P**roject administration
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CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

This study followed the ethical principles of educational research and was formally approved by the Ethics Committee of Karaganda National Research University named after Academician E.A. Buketov, Karaganda, Kazakhstan. Before data collection began, the committee reviewed and approved the research protocol, including the study objectives, methodology, and research instruments, such as the questionnaire and structured interviews.

DATA AVAILABILITY

The data supporting the findings of this study are available from the corresponding author, [AD], upon reasonable request.

REFERENCES

[1] L. Sabyrkhanova, L. Zhaidakbayeva, M. A. Sözer, D. Belessova, Z. Kurmanbayeva, and A. Zhidebayeva, "Digital literacy as a tool for developing computational thinking in young learners: a literature review," *Open Education Studies*, vol. 8, no. 1, Jun. 2026, doi: 10.1515/edu-2025-0121.

[2] A. Karymsakova, G. Kapbar, K. Berkimbayev, and G. Bakirova, "A practice-oriented approach to teaching python programming for university students," *Open Education Studies*, vol. 7, no. 1, Jan. 2025, doi: 10.1515/edu-2025-0099.

[3] K. Berkinbayeva, "Methods of implementing mobile learning applications in the training of future computer science teachers," *Periodicals of Engineering and Natural Sciences (PEN)*, vol. 13, no. 4, pp. 965–976, Dec. 2025, doi: 10.21533/pen.v13.i4.780.

[4] G. Abildinova, T. Sembayev, and K. Mukhtarkyzy, "Enhancing computer science education: student insights on active learning and digital integration," *World Transactions on Engineering and Technology Education*, vol. 22, no. 4, pp. 299–305, 2024.

[5] U. Abdigapbarova, D. Sadirbekova, S. Nishanbayeva, and N. Zhiyenbayeva, "The impact of digital hybrid education model on teachers' engagement and academic performance in the context of Kazakhstan," *Scientific Reports*, vol. 15, no. 1, May 2025, doi: 10.1038/s41598-025-02875-2.

[6] G. B. Sarzhanova, R. S. Bobesh, G. Z. Smagulova, A. Turkel, and N. B. Serikbayeva, "Instructional design of smart technology use in teacher digital educational environment," (in Russian), *The Education and Science Journal*, vol. 25, no. 9, pp. 197–230, Nov. 2023, doi: 10.17853/1994-5639-2023-9-12-45.

[7] K. K. F. Yuen, D. Y. W. Liu, and H. V. Leong, "Competitive programming in computational thinking and problem solving education," *Computer Applications in Engineering Education*, vol. 31, no. 4, pp. 850–866, Jul. 2023, doi: 10.1002/cae.22610.

[8] L. H. González-Guerra, M. Y. Burgos-Lopez, and C. E. C. Mondragon, "Transforming engineering education with competitive programming, gamified learning, and AI-Driven innovation," in *2025 World Engineering Education Forum-Global Engineering Deans Council (WEEF-GEDC)*, IEEE, Sep. 2025, pp. 1–8. doi: 10.1109/WEEF-GEDC66748.2025.11256488.

[9] M. M. Haqqani, G. B. Regulwar, B. A. Goud, S. P. Veggalam, K. Prakash, and E. R. Kumar, "Enhancing remote learning by using competitive coding platform," in *2024 IEEE North Karnataka Subsection Flagship International Conference (NKCon)*, IEEE, Sep. 2024, pp. 1–6. doi: 10.1109/NKCon62728.2024.10774847.

[10] K. Oyetade, T. Zuva, and A. Harmse, "Evaluation of the impact of hackathons in education," *Cogent Education*, vol. 11, no. 1, Dec. 2024, doi: 10.1080/2331186X.2024.2392420.

[11] P. Guo, N. Saab, L. S. Post, and W. Admiraal, "A review of project-based learning in higher education: Student outcomes and measures," *International Journal of Educational Research*, vol. 102, 2020, doi: 10.1016/j.ijer.2020.101586.

[12] M. Mukanova, Y. Daineko, A. Yerzhanova, V. Manasheva, and G. Bessenbayeva, "The use of IoT technologies in STEM laboratories using the example of Nazarbayev Intellectual Schools," *Procedia Computer Science*, vol. 272, pp. 508–513, 2025, doi: 10.1016/j.procs.2025.10.239.

[13] R. Yilmaz and F. G. Karaoglan Yilmaz, "Augmented intelligence in programming learning: examining student views on the use of ChatGPT for programming learning," *Computers in Human Behavior: Artificial Humans*, vol. 1, no. 2, Aug. 2023, doi: 10.1016/j.chbah.2023.100005.

[14] R. Sajja, Y. Sermet, B. Fodale, and I. Demir, "Evaluating AI-powered learning assistants in engineering higher education with implications for student engagement, ethics, and policy," *Scientific Reports*, vol. 16, no. 1, Feb. 2026, doi: 10.1038/s41598-026-39237-5.

[15] E. Kasneci *et al.*, "ChatGPT for good? On opportunities and challenges of large language models for education," *Learning and Individual Differences*, vol. 103, Apr. 2023, doi: 10.1016/j.lindif.2023.102274.

[16] Y. Wan, R. Li, W. Li, and H. Du, "Impact pathways of AI-supported instruction on learning behaviors, competence development, and academic achievement in engineering education," *Sustainability*, vol. 17, no. 17, Sep. 2025, doi: 10.3390/su17178059.

[17] M. X. Y. Tan, Y. Qu, and J. Wang, "Student perceptions of generative artificial intelligence regulations: a mixed-methods study of higher education in Singapore," *Higher Education Quarterly*, vol. 79, no. 3, Jul. 2025, doi: 10.1111/hequ.70038.

[18] O. Karnalim, H. Toba, M. C. Wijanto, Y. D. Setiawan, N. Surantha, and M. Liut, "Detecting GenAI assistance in programming assessments with over-uniqueness and sample matching," *Discover Computing*, vol. 29, no. 1, Jan. 2026, doi: 10.1007/s10791-025-09884-9.

[19] M. Alfaleh, "Sustainable AI-Driven assessment in higher education: a systematic review of fairness, transparency, pedagogical innovation, and governance," *Sustainability*, vol. 18, no. 2, Jan. 2026, doi: 10.3390/su18020785.

[20] J. Luo, C. Zheng, J. Yin, and H. H. Teo, "Design and assessment of AI-based learning tools in higher education: a systematic review," *International Journal of Educational Technology in Higher Education*, vol. 22, no. 1, Jul. 2025, doi: 10.1186/s41239-025-00540-2.

[21] C. Zhao, "AI-assisted assessment in higher education: A systematic review," *Journal of Educational Technology and Innovation*, vol. 6, no. 4, Jan. 2025, doi: 10.61414/jeti.v6i4.209.

[22] M. Abrar, W. Aboraya, R. A. Khaliq, K. P. Subramanian, Y. Al Husaini, and M. Al Husaini, "AI-powered learning pathways: personalized learning and dynamic assessments," *International Journal of Advanced Computer Science and Applications*, vol. 16, no. 1, 2025, doi: 10.14569/IJACSA.2025.0160145.

[23] V. Lavanya, J. Jelina, S. Swetha, and T. J. B. V. Varshini, "Personalized AI based learning path generator using adaptive skill assessment," in *2025 9th International Conference on Electronics, Communication and Aerospace Technology (ICECA)*, IEEE, Nov. 2025, pp. 1950–1955. doi: 10.1109/ICECA66444.2025.11382869.

[24] D. Pramod, "Decoding responsible AI use: the influence of digital literacy and ethical awareness," *Cogent Education*, vol. 12, no. 1, Dec. 2025, doi: 10.1080/2331186X.2025.2592371.

[25] M. T. Siddiqui, "AI-Enabled pedagogy: advancing education through innovative teaching tools and the AI-TEACH model," *Journal of Informatics Education and Research*, vol. 5, no. 1, Mar. 2025, doi: 10.52783/jier.v5i1.2261.

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