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Integration of SAMR, TPACK, and Artificial Intelligence in Computer Science Teacher Education: Impact on Academic Achievement and Digital Competencies

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***Abstract*—The rapid digital transformation of teacher education requires instructional models that integrate established pedagogical frameworks with emerging Artificial Intelligence (AI) tools. This study investigates the effectiveness of a unified Substitution, Augmentation, Modification, Redefinition-Technological Pedagogical Content Knowledge-Artificial Intelligence (SAMR–TPACK–AI) framework for enhancing learning outcomes among pre-service computer science teachers. A quasi-experimental design was implemented with over 150 participants across control and experimental groups, using validated instruments and mixed-methods analysis (Analysis of Covariance (ANCOVA), Linear Mixed Model (LMM)). Findings demonstrate significant gains in the experimental group: academic performance increased by 12.2 percentage points, motivation by 0.52 points, and digital competencies by 14.9 points. Cross-disciplinary outcomes also improved, including critical thinking and teamwork skills. The results provide empirical validation of the integrated SAMR–TPACK–AI framework as an effective digital learning design. The study offers a novel conceptual contribution to AI-enhanced digital pedagogy and provides practical implications for developing sustainable, future-oriented teacher education programs.**

***Keywords*—Substitution Augmentation Modification Redefinition (SAMR), Technological Pedagogical Content Knowledge (TPACK), artificial intelligence, digital competencies, teacher education, computer science**

I. INTRODUCTION

The current stage of educational development is characterized by the rapid integration of digital technologies, driven by global digitalization processes and the urgent need to prepare competitive specialists in the information society. In this context, the enhancement of methodological training for future computer science teachers becomes particularly relevant, as their professional activity is directly associated with the use and transformation of digital tools in the learning process [1]. Teacher education for the new generation should not only ensure mastery of basic Information Communication Technologies (ICT) skills but also foster the ability to apply innovative instructional models, integrate Artificial Intelligence (AI) tools, and develop methodological competencies that guarantee high-quality teaching and learning. In recent years, the academic literature has increasingly focused on the Substitution, Augmentation, Modification, Redefinition (SAMR) and Technological Pedagogical Content Knowledge (TPACK) models, which provide structured frameworks for implementing technology into pedagogical practice while ensuring a balance between content, methodology, and digital tools. However, despite the wide recognition of these models, their practical application in computer science teacher education remains underexplored, particularly in the context of AI integration. Empirical evidence is needed to confirm the effectiveness of these approaches within local educational programs [2].

The study was conducted on the experimental base of M. Auezov South Kazakhstan University and South Kazakhstan Pedagogical University, involving more than 150 second- and third-year undergraduate students enrolled in the "Informatics" (6B01530) and "Mathematics–Informatics" (6B01531) programs. Particular attention was given to the courses Theoretical Foundations of Informatics and Theoretical Issues of Informatics, where the integration of digital learning models and artificial intelligence tools made it possible to observe changes in students' academic performance, motivation, and critical thinking. The aim of the study is to evaluate the effectiveness of an integrated SAMR–TPACK framework enhanced with AI tools in improving academic performance, motivation, digital competence, and higher-order skills among future computer science teachers. The novelty of the research lies in empirically validating the combined use of SAMR, TPACK, and AI within the national teacher-education context, and in demonstrating how this integrated model can serve as a structured digital learning design applicable to pre-service teacher training.

This research offers two interrelated contributions. The theoretical contribution lies in the development of the integrated SAMR–TPACK–AI conceptual framework, which aligns the hierarchical structure of SAMR (from Substitution to Redefinition) with the TPACK components (content, pedagogy, technology) and incorporates the functional capabilities of AI tools, such as adaptive systems, chatbots, and automated assessment. This framework not only captures the depth of technological integration but also elucidates the mechanisms through which specific AI functionalities shape pedagogical decisions and instructional content. The practical contribution is reflected in translating this framework into a functional template for a digital

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teaching project for pre-service informatics teachers. This template includes a modular lesson design structured by SAMR levels, TPACK-based pedagogical justification, the selection of appropriate AI resources, and accompanying assessment rubrics. The proposed approach facilitates the adoption of the methodology in teacher education programs, promotes reflective decision-making in technology use, and provides ready-to-implement components for designing tasks at the Modification and Redefinition levels while ensuring academic integrity when applying AI tools.

II. LITERATURE REVIEW

The issue of developing teachers' digital competence remains a methodological backbone for studies on the integration of Educational Technologies (EdTech) and Artificial Intelligence (AI). The European framework DigCompEdu [3] outlines six domains of competence (ranging from professional engagement to assessment and learner empowerment) and is widely used as a reference in the design of teacher education programs. The most recent edition, published by the Joint Research Centre of the European Commission [4], confirms both the stability of the framework and its strong applied orientation for teacher professional development planning. At the same time, the broader civic framework DigComp is evolving toward version 3.0 (scheduled for release by the end of 2025), reflecting the ongoing renewal of digital competence indicators relevant also for future computer science teachers [4]. Complementing this picture are international reviews of digital competence frameworks by UNESCO-UNEVOC [5], which emphasize their updates in 2022–2023 and highlight the increasing unification of terminology.

Between 2019 and 2024, the SAMR model has remained one of the most frequently used frameworks for analyzing the depth of technology integration (from substitution to redefinition). A recent systematic review (2019–2024) documented steady growth in related research and emphasized that the strongest effects on learning outcomes are typically achieved at the Modification and Redefinition levels, whereas Substitution/Augmentation yield only modest gains. Empirical evidence supports these conclusions: a recent study published in [6] reported statistically significant differences in student achievement between experimental and control groups when all SAMR levels were systematically implemented with modern IT tools [7]. In the broader Technology-Enhanced Learning (TEL) context, SAMR is used as a "diagnostic lens" to evaluate whether teachers truly capitalize on the potential of technologies—an argument confirmed by a recent systematic review of TEL learning activities.

Regarding TPACK, a series of review and meta-analytic studies has appeared in 2024–2025. A major "review of reviews" published in [8] demonstrated the maturity of the field while pointing out methodological inconsistencies in the operationalization of constructs, which hinder comparability of measurements and outcomes across teacher education programs. This is complemented by a 2024 meta-analytic study (systematic review + meta-analysis), where both qualitative and quantitative evidence converges to support the positive impact of TPACK-based interventions on teaching practices and pre-service teachers' confidence in ICT integration. Earlier, a systematic review in [9] also highlighted that the strongest learning shifts occur when the technological component is embedded into pedagogy and subject content, rather than taught in isolation.

Recent systematic reviews highlight the dual effect of AI in education: when properly integrated, it produces significant gains in personalization and learning outcomes, but insufficient preparation can lead to risks related to ethics, dependence, and assessment bias. A review [10] documents improvements in achievement and motivation when using Artificial Intelligence in Education (AIED) and adaptive learning systems, while emphasizing the critical role of pedagogical design and teacher preparation [11]. A comprehensive SLR covering 2024–2025, including publications in [12], systematizes empirical findings from 2023–2024 and notes a paradigm shift from the "ban/not ban" debate toward strategies of meaningful integration and higher-order assessment. A meta-analysis of 51 studies (2022–February 2025) published in [12] demonstrates an overall positive effect of ChatGPT on academic achievement and learning perception, but also points to heterogeneity of outcomes depending on subject area and task design.

The 2023 report of the U.S. Department of Education stresses practices of "human-in-the-loop", transparency, assessment, and the development of AI literacy among teachers and students, providing a policy framework for safe and effective AI integration [13]. At the intersection of SAMR and AI, applied studies are emerging: for instance, evaluations of learning outcomes using AI platforms through the lens of SAMR levels demonstrate both achievement gains and positive student perceptions of transformed activities [14]. Finally, a review [15] of AI in teaching and teacher professional development (2015–2024) underlines that the key moderator of outcomes is systemic teacher support and preparation, rather than the choice of a particular AI tool.

An important direction of the current digital transformation of education is the use of Artificial Intelligence (AI) tools, which are gradually becoming an integral part of preparing future computer science teachers. There are different categories of such tools, each serving its unique function and having both advantages and limitations. In particular, chatbots and virtual assistants (e.g., ChatGPT, Bing AI) provide students with explanations of theoretical concepts, step-by-step problem solutions, programming code examples, and even personalized consultations. Adaptive learning systems (such as Codewars, HackerRank) are designed for automatic adjustment of task complexity, gamification of the learning process, and the development of independent learning skills [16].

Automated testing and task generation tools (e.g., GitHub Copilot) play a special role by saving teachers' time and supporting practice-oriented learning, though they may reduce students' level of independence. Educational analytics systems (Moodle with AI plugins, Google Classroom with AI-based analytics) make it possible to monitor student activity, identify problem areas, and adjust the learning process in real time, although they require specific data literacy skills and raise concerns related to privacy [17].

To systematize and summarize these approaches, a comparative table has been prepared that reflects the main categories of AI tools, their functions, strengths, and potential risks (Table 1). Table 1 provides a comparative overview of AI tools relevant to teacher education in computer science. It outlines representative examples, core functions, and both benefits and limitations, offering a balanced perspective on their potential role in enhancing digital competence and teaching practice.

Table 1. Comparative overview of AI tools in computer science teacher education

Tool Category	Examples	Main Functions	Advantages	Limitations/Risks
Chatbots and virtual assistants	ChatGPT, Bing AI	Explanation of theory and concepts -Step-by-step solution of problems -Generation of code examples -Personal consultation	-24/7 availability -Increased engagement -Individualization of learning - Quick feedback	-Risk of dependence on hints -Possibility of errors in answers -Requires critical evaluation of information -Problems with academic integrity
Adaptive learning systems	Code wars, Hacker Rank	Setting programming tasks -Automatic adaptation of complexity -Gamification of learning -Automatic code checking -Generation of tasks and tests -Hints on error correction	-Personalization of trajectories -Stimulation of independent work	Requires digital literacy of students -Possible technical complexity -Less attention to humanitarian aspects (motivation, teamwork)
Tools for automated testing and task generation	GitHub Copilot	Automatic code checking -Generation of assignments and tests -Hints for error correction	-Development of algorithmic thinking skills -Saving teacher time -Quick correction of errors -Support for practice-oriented learning	-May form a habit of “trusting the machine” in students -Limited depth of analysis -Potential decrease in independence
Systems for analyzing educational data	Moodle with AI plugins, Google Classroom + AI analytics	-Tracking of student activity -Analysis of engagement -Identification of problem areas of learning	-Objectivity of analysis -Possibility of course adjustments “on the go” -Improved management of the educational process	-Requires skills in working with analytics -Data privacy issues may arise -Does not always take into account motivational and psychological

Recent empirical studies highlight the pedagogical value of integrating the SAMR and TPACK frameworks alongside AI-based tools, demonstrating that such a hybrid approach provides a more comprehensive structure for technology-enhanced learning. Hambabi *et al.* [18] conducted an empirical investigation of a hybrid SAMR–TPACK model in real classroom settings and found that teachers, despite possessing solid TPACK knowledge, struggled to advance beyond enhancement-level uses of technology without explicit structural guidance. They showed that when AI-supported platforms and LMS environments (e.g., Google Classroom) were embedded within the hybrid model, teachers were more capable of transforming learning tasks in alignment with the upper levels of SAMR. This finding underscores that meaningful transformation requires not only Technological Pedagogical Content Knowledge (TPACK) but also a clear framework for depth of integration (SAMR) supported by AI-driven tools.

Additionally, empirical evidence suggests that the integration of AI within TPACK-based instructional design requires expanded competencies not fully captured in traditional models. Çelik *et al.* [19] demonstrated that teachers' Technological Knowledge (TK), Technological-Pedagogical Knowledge (TPK), and ethical-AI assessment skills were significant predictors of their readiness to implement AI tools responsibly in the classroom. Their results indicate that even when SAMR provides a structure for the progression from substitution to redefinition, teachers' ability to deploy AI in pedagogically sound and ethically informed ways depends on enhanced forms of TPACK knowledge. Consequently, the literature suggests that the combined SAMR–TPACK–AI perspective offers a more robust and empirically grounded framework for guiding AI-supported instructional innovation.

Overall, the reviewed literature demonstrates a consensus on three key points: the DigCompEdu/DigComp and TPACK frameworks provide a reliable basis for conceptualizing and measuring teacher competences; the upper levels of the SAMR model (Modification and Redefinition) are consistently associated with stronger educational effects; and the positive impact of AI and generative AI emerges primarily when they are integrated through pedagogically meaningful design, supported by teacher training and institutional policies. These findings justify the combined approach adopted in this study—integrating SAMR and TPACK with AI tools in the preparation of future computer science teachers and analyzing their effects not only on academic performance but also on motivation and the development of digital competences [20]. At the same time, the comparative analysis of AI tools (Table 1) highlights both their potential and their risks, underscoring the need to combine technical proficiency with methodological readiness for critical and responsible application. These trends form the foundation for the development of the research methodology, which presents the experimental design, sample, and analytical methods employed.

III. MATERIALS AND METHODS

A. *Design of the Study*

This study employed a quasi-experimental design aimed at examining the impact of the SAMR and TPACK digital models, combined with Artificial Intelligence (AI) tools, on the preparation of future computer science teachers. The experiment was conducted over one semester during the 2023–2024 academic year. The study was conducted in accordance with the ethical guidelines of M. Auezov South Kazakhstan University and South Kazakhstan Pedagogical University. Institutional approval was obtained prior to data collection, and all participants provided informed consent. Participation was voluntary, and students were assured of confidentiality and the anonymization of all collected data.

To ensure comparability of results, participants were divided into control and experimental groups. Instruction in the experimental group was structured around the SAMR and TPACK models with the active integration of chatbots (ChatGPT, Bing AI), adaptive learning systems (Codewars, HackerRank), automated code-checking tools (GitHub Copilot), and educational analytics platforms (Moodle with AI plugins, Google Classroom with AI-based analytics). The control group continued learning through traditional methods, which allowed for the identification of differences in academic performance, motivation, and the development of digital competences [21].

The research design comprised four consecutive stages (see Figs. 1–3):

- Preparatory stage—literature review, development of diagnostic instruments (questionnaires, tests, checklists), formation of groups, and appointment of supervising instructors.
- Baseline stage—initial knowledge testing, primary survey (motivation, digital competences), and observation of the traditional learning process.
- Formative stage (experiment)—integration of SAMR and TPACK into lesson design, use of chatbots, adaptive systems, Copilot, and Moodle analytics, with the experimental group engaged in a digital learning environment.
- Control stage—final testing and repeated survey, comparison of results between control and experimental groups, and both statistical and qualitative data analysis.

This design made it possible not only to evaluate the direct impact of digital models and AI tools on students' academic performance but also to capture changes in their motivation, digital competences, as well as the development of critical thinking and teamwork skills [22].

The presented diagrams reflect the logic and sequence of the conducted study. Fig. 1 illustrates the overall research structure, including theoretical analysis, methodological development, experimental implementation, and result analysis. Fig. 2 visualizes the experimental design, comparing the control group, which studied through the traditional model, with the experimental group, where SAMR, TPACK, and artificial intelligence tools were applied. Fig. 3 depicts the process of integrating the SAMR and TPACK models, showing how they complement each other and form the foundation for the effective use of digital technologies and AI in the educational process. Taken together, these diagrams provide a clearer understanding of the relationship between the methodology, the organization of the study, and the key pedagogical models.

This diagram (Fig. 1) outlines the general structure of the study, including theoretical analysis, methodological development, experimental implementation, and the subsequent analysis of results. It provides a holistic view of the research logic and its main stages.

Fig. 2 visualizes the quasi-experimental design, contrasting the control group, which studied through a traditional approach, with the experimental group, where SAMR, TPACK, and AI tools were integrated. The design highlights the comparative logic underlying the study.

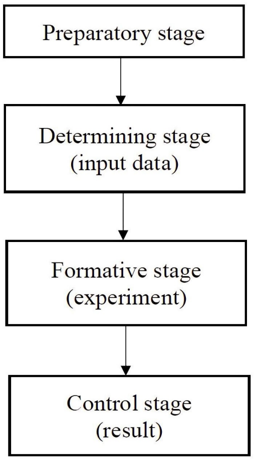

Fig. 1. Overall research framework.

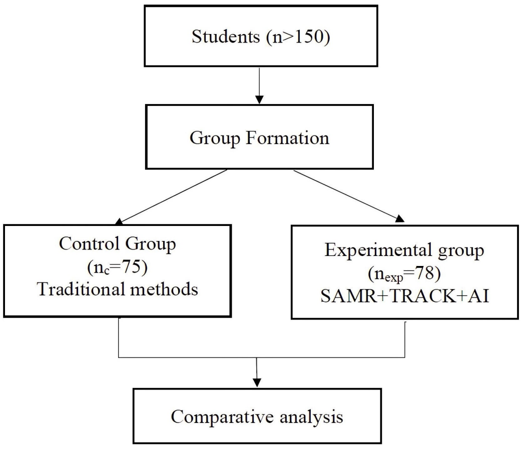

Fig. 2. Experimental design (comparison of groups).

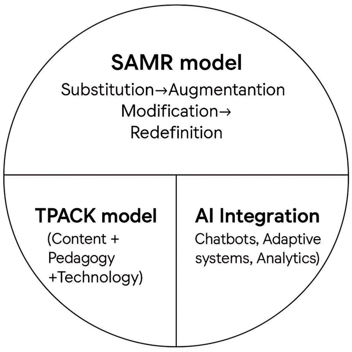

Fig. 3. Integration of the SAMR and TPACK models.

This illustration (Fig. 3) demonstrates how SAMR and TPACK complement each other, forming a methodological foundation for the effective integration of digital technologies and AI in teacher education. It emphasizes their combined role in enhancing teaching practices and learning outcomes. The main feature of this study lies in its combined approach: not only is the effectiveness of the SAMR and TPACK models examined individually, but their joint application together with modern AI tools is also analyzed. This design makes it possible to assess the extent to which digital transformation can fundamentally reshape the preparation of future computer science teachers [23].

B. Instruments

The experimental group showed clear positive trends in academic achievement, learning motivation, and the development of digital competencies. Special attention was also given to cross-disciplinary outcomes such as critical thinking and teamwork skills, which were incorporated into the instructional design. The methodological framework was structured to assess the contribution of the SAMR and TPACK digital learning models, complemented by AI-based tools, to the preparation of future computer science teachers. The experimental work was conducted during the 2023–2024 academic year at M. Auezov South Kazakhstan University and the South Kazakhstan Pedagogical University, involving second- and third-year students enrolled in the Computer Science and Mathematics–Computer Science programs. All procedures followed institutional ethical guidelines, and data were collected through achievement assessments, validated questionnaires, and structured classroom observations, allowing for a comprehensive evaluation of the intervention's impact. The study consisted of several sequential stages. At the preparatory stage, a review of scientific literature was conducted, and diagnostic instruments were developed, including questionnaires to assess student motivation and digital literacy, tests to evaluate academic achievement, and checklists for systematic observation of the learning process. During this stage, the experimental and control groups were also formed to ensure comparability of results. At the baseline stage, students underwent entry testing in the courses "Theoretical Foundations of Informatics" and "Theoretical Issues of Informatics", alongside a survey designed to determine their initial levels of digital competence and learning motivation. At the same time, observations of traditional classes were conducted, which made it possible to capture the baseline level of student engagement and readiness for teamwork [24, 25].

The formative phase was dedicated to integrating the SAMR and TPACK models into the educational process, in combination with the use of Artificial Intelligence (AI) tools. For the experimental group, lessons were designed to follow the staged progression of SAMR levels—from the simple substitution of traditional tasks with digital equivalents to the complete redefinition of learning tasks using AI. Simultaneously, the TPACK framework was implemented to ensure a harmonious integration of technological, pedagogical, and content knowledge components. AI tools included chatbots for programming practice, automated code-checking systems, and online services for task generation and feedback provision. While the control group continued learning through traditional methods, the experimental group engaged in a transformed digital learning environment [26, 27].

During the control phase, final testing and follow-up student surveys were conducted, and the results of both groups were compared. Special attention was paid to changes in academic performance, motivational dynamics, as well as the development of critical thinking and teamwork skills. Both quantitative and qualitative analyses were employed. Quantitative analysis involved the calculation of mean values, percentage changes, and the application of statistical tests (e.g., Student's t-test) to assess the significance of differences. Qualitative analysis focused on interpreting survey data and observations, as well as identifying pedagogical effects that could be associated with SAMR levels and TPACK components [28, 29].

The methodological framework was designed to evaluate whether the integration of the SAMR and TPACK models with AI-based tools could lead to measurable improvements in students' academic performance, learning motivation, digital competencies, and collaborative skills. The novelty of this approach lies in combining these pedagogical models within a unified instructional design and applying them in a real university setting. This integration was expected to produce moderate gains in learning outcomes, consistent with previous studies [30–32].

During the formative phase, particular emphasis was placed on the selection and testing of AI tools tailored to educational tasks. The experimental group employed a set of AI services that can be categorized into four main types:

1) Chatbots and virtual assistants

To support students' independent learning, intelligent chatbots such as ChatGPT and its analogs were employed. These tools provided answers to questions, explained theoretical concepts, and offered additional exercises. Their use enabled the organization of individualized learning trajectories, accelerated feedback, and increased student engagement. Importantly, the chatbots were not used to directly solve tasks but to explain underlying logic, guide step-by-step reasoning, and generate code examples, thereby minimizing the risk of academic dishonesty.

2) Adaptive learning systems

In programming and theoretical computer science courses, platforms such as Codewars, HackerRank, and locally adapted simulators were utilized. These systems automatically adjusted the difficulty level of tasks based on student performance. They allowed the implementation of the higher levels of the SAMR model, as assignments were dynamically adapted according to student progress, providing personalized practice opportunities.

3) Automated code-checking and task generation tools

AI-based services capable of analyzing student code and providing instant feedback were applied. For example, GitHub Copilot was used for code suggestions and autocompletion, which accelerated the completion of laboratory assignments, while integrated code analysis tools detected errors and suggested corrections. AI-powered test question generators were also employed to automate the creation of exercises of varying complexity, streamlining the learning process [33].

4) Learning analytics systems

To monitor learning effectiveness and student activity, AI tools integrated into learning management platforms (e.g., Moodle, Google Classroom with additional analytical plugins) were employed. These tools collected data on task completion time, engagement levels, and academic performance trends. This enabled instructors to obtain objective metrics and promptly adjust the educational process.

A mixed-methods approach, combining both quantitative and qualitative analysis, was employed to comprehensively test the research hypotheses. Specifically, surveys were used to assess students' learning motivation and attitudes toward digital technologies; comparative knowledge testing was conducted in control and experimental groups; student behavior in classrooms was observed; and statistical analyses were performed to examine differences between groups. Additionally, AI tools (chatbots, online assistants, adaptive systems) were integrated into the study, allowing the evaluation of their contribution to enhancing learning quality and developing digital competencies [34, 35].

The systematization of the applied methods is presented in Table 2, which includes input data, expected outcomes, a description of each method, as well as its advantages and limitations. This overview demonstrates that the study maintained a balance between objective quantitative measurements (tests, surveys, statistics) and more flexible qualitative procedures (observations, work with AI tools). Such an approach increased the validity and robustness of the obtained results.

Table 2. Summary of research methods

Method	Input data	Output data	Method description	Advantages	Disadvantages
Questionnaire	Answers of 2nd-3rd year students to questions about motivation, perception of ICT and AI in education	Level of learning motivation, attitude towards technology, self-assessment of digital competencies	Developed questionnaires with open and closed questions were used to assess the perception of SAMR, TPACK and AI	Rapid acquisition of large amounts of data; ability to identify subjective attitudes; statistical processing	Subjectivity of assessment risk of “socially desirable’ responses; limited depth o analysis
Comparative knowledge testing	Results of control and experimental groups in th disciplines “Informatics theory” and “Informatics theory”	Change in academic performance (in %); learning of educational material	Students were tested before and after the implementation of SAMR, TPACK and AI tools	Objective assessment of academic results; ability to compare “before” and “after”	Requires standardization of tests; does not always reflect the development of high-order skills
Observation	Students’ behavior in class: activity, involvement in discussions, participation in teamwork	Level of engagement, development of critical thinking, teamwork skills	Systematic observation of classroom work and the use o digital tools (online platforms chatbots, simulators)	Allows recording “live” learning dynamics; identifies hidden factors of engagement	Observer subjectivity; takes time; difficult to process large groups
Comparative group analysis	Experimental group (us SAMR, TPACK, AI) an control group (tradition approach)	Differences in motivation, academic performance, digital competencies	Comparison of the results of two groups using statistical methods (average values, % changes)	Allows identification of cause-and-effect relationships; increases the reliability of results	Requires strict control of experimental conditions; possible heterogeneity of groups
Integration of AI tools	Using chatbots, online assistants, adaptive systems in educational tasks	Increased independence, faster feedback, increased quality of projects	Use of AI for automatic checking of assignments, generation of examples, personalization of training	High practical value; accelerates learning; develops digital literacy	

To make the data structure fully transparent and replicable, the key variables used in the study, together with their measurement types and primary data sources, are summarized in Table 3.

Table 3. Key variables, measurement scales, and data sources

Variable	Measurement Type	Scale	Data Source
Academic Achievement	Cognitive outcome	Standardized test	Final assessment developed by course instructors
Motivation	Affective outcome	Likert-type	Validated motivation questionnaire
Digital Competence	Professional/technical outcome	Composite index	Adapted DigCompEdu indicators
Critical Thinking	Cross-disciplinary skill	Rubric	Expert evaluation (two raters)
Teamwork	Cross-disciplinary skill	Rubric	Expert evaluation (two raters)
Qualitative Data	Experience-based insights	Thematic units	Open-ended responses, observation notes, instructor interviews

The implementation of AI tools enabled a significant improvement in feedback quality, personalized learning, and the development of skills demanded in the digital economy. Furthermore, the use of adaptive systems and intelligent assistants facilitated the practical integration of the SAMR and TPACK models, transforming digital technologies from auxiliary tools into key drivers of the educational process.

Nevertheless, the study also considered certain limitations. These included potential student dependency on chatbot prompts, the risk of reduced autonomy in task completion, and the need for additional instructor training to ensure the proper use of AI resources. Special attention was given to academic integrity: to minimize violations, AI was employed as a supportive tool rather than a means of completing assignments on behalf of students.

Thus, the use of specific AI tools made the study not only theoretically grounded but also practically meaningful, creating conditions for the transition from traditional teaching methods to transformed digital practices in the training of future computer science teachers.

C. *Data Analysis*

To validate the research hypotheses, an analytical framework was developed that combined the assessment of statistical differences, effect size estimation, and sample size power calculation. The main hypotheses are formulated as follows (Table 4).

Reliable metrics were employed to test these hypotheses: standardized final tests with a reliability coefficient ≥0.80, validated motivation questionnaires (Cronbach’s $\alpha \geq 0.75$, group invariance confirmed via CFA), a digital competence index (0–100), and expert rubrics with inter-rater agreement ensured by $k \geq 0.70$.

The analysis proceeded as follows. In the first step, the equivalence of the control and experimental groups on baseline data was assessed using t-tests and χ^2 tests. Any detected differences were controlled for in an ANCOVA model, where the post-test score served as the dependent variable, and the pre-test score along with additional factors (e.g., class or instructor) were included as covariates. In cases of hierarchical data nesting, a Linear Mixed Model (LMM) with random intercepts for classes and instructors was applied. The primary coefficient of interest was the "group = EG" parameter [36–38].

Table 4. Formulation of research hypotheses and expected intervention effects

Hypothesis	Description
H1	After the intervention, the mean test score of students in the experimental group (EG) is expected to exceed that of the control group (CG) by 10–14 percentage points on a 0–100 scale.
H2	The mean learning motivation index in the EG is expected to be 15–20% higher, corresponding to an increase of approximately $\Delta \approx$ 0.4–0.6 points on a 1–5 Likert scale.
H3	The mean digital competence index (0–100), calculated using adapted DigCompEdu indicators, is expected to increase in the EG by 12–20 points.
H4	According to expert rubrics for critical thinking and teamwork (0–4 scale), the experimental group is expected to demonstrate an improvement of at least 0.5–0.8 points.

Power calculations showed that for academic performance, assuming $\sigma = 15$ and an expected $\Delta = 12$ percentage points, approximately 25 participants per group would be sufficient to achieve 80% power, and around 33 participants for 90% power. For scenarios with $\sigma = 18$ and $\Delta = 14$ points, about 26 participants per group would ensure 80% power. For motivation measured on a 1–5 Likert scale, with $\sigma = 0.7$ and an expected difference of $\Delta = 0.5$, 30–33 participants per group were sufficient. For digital competence indices (0–100), with $\sigma = 15$ and an expected $\Delta = 15$, approximately 25 participants per group met the required threshold. Given that the study involved over 150 students, the actual sample size (70–80 participants per group) substantially exceeded the minimum power requirements.

To evaluate cross-disciplinary outcomes such as critical thinking and teamwork, expert rubrics with independent double scoring were employed. Depending on scale properties, analyses were conducted using ordinal logistic regression or t-tests/ANCOVA; effect sizes were calculated using Cliff's δ or Hedges' g. Statistical significance was established using Holm-adjusted $p < 0.05$ for two rubric-based outcomes, with an improvement of at least 0.5 points and 95% confidence intervals excluding zero.

Internal validity was ensured through multiple procedures: (a) teacher effects were modeled using linear mixed-effects models (LMM), (b) baseline differences were statistically controlled by including pre-test values as covariates, (c) academic integrity safeguards were implemented when working with AI tools (e.g., requiring explanations instead of ready-made answers, originality checks, oral verification), and (d) reliability of instruments was confirmed (Cronbach's $\alpha \geq 0.75$ for motivation indices; ICC ≥ 0.70 for rubric assessments).

The analytical logic was as follows: hypotheses H1–H3 were considered supported if ANCOVA or LMM models produced adjusted p-values < 0.05, confidence intervals for EG–CG differences excluded zero, and effect sizes exceeded Hedges' $g = 0.5$, with convergence across robustness checks. Hypothesis H4 was evaluated analogously for rubric-based outcomes. This framework ensured that the expected intervention effects could be rigorously and transparently assessed [39, 40].

In addition to the quantitative procedures, the study incorporated a qualitative component designed to provide a deeper understanding of students' experiences and the pedagogical effects of integrating the SAMR–TPACK framework with AI-based tools. The qualitative data included open-ended questionnaire responses, field notes from structured classroom observations, and transcripts of brief teacher interviews/discussions (see Instruments section).

The analysis followed several iterative stages grounded in the principles of Braun and Clarke [41] thematic analysis: (1) familiarization with the data and its transcription/organization; (2) identification of meaningful units and initial coding (inductively—from the data—and deductively—based on predefined categories aligned with SAMR and TPACK components); (3) development of a coding hierarchy and consolidation of codes into thematic clusters; (4) review and refinement of themes through secondary recoding; and (5) interpretation of the themes and their comparison with quantitative findings.

To enhance coding reliability, two independent researchers coded the same subset of data. Discrepancies were discussed and resolved through consensus, after which the codebook was refined and applied to the full dataset. Inter-coder agreement was assessed statistically (Cohen's κ / percent agreement) and exceeded the acceptable threshold adopted for rubric-based evaluations in the study. Internal validity was strengthened through source triangulation: themes derived from open responses were cross-checked against observational records and expert rubric scores (critical thinking and teamwork). An audit trail documenting analytic decisions was maintained, and selected interpretations were verified through a brief member-check with participating instructors to confirm accuracy and credibility.

Overall, the qualitative analysis complemented the quantitative results by clarifying the mechanisms underlying the observed changes—for example, how and under what conditions AI-based tools enhanced learning motivation or supported the development of critical thinking. This integration of methods increased the interpretive depth and credibility of the study's conclusions.

IV. RESULTS

The experimental study was conducted on a sample of education-major students ($n > 150$), divided into control and experimental groups. The control group received traditional instruction, while the experimental group was taught using the SAMR and TPACK digital models supplemented with artificial intelligence (AI) tools. Table 5 provides a concise synthesis of the intervention effects (EG–CG differences) with 95% confidence intervals and qualitative interpretation. Detailed descriptive statistics (M±SD), p-values and effect-size estimates are reported in Table A1 (Appendix).

Analysis of the cross-disciplinary outcomes revealed that the experimental group outperformed the control group in critical thinking and teamwork by 0.5–0.8 points ($p < 0.05$), as confirmed by both ordinal logistic regression and robustness checks.

The overall conclusion is that all primary hypotheses (H1–H3) were supported by statistically significant differences ($p < 0.05$) with medium-to-large effect sizes, and hypothesis H4 was confirmed based on expert evaluations. Thus, the integration of the SAMR and TPACK digital models combined with AI tools proved effective, resulting in substantial improvements in academic performance, learning motivation, digital competencies, as well as the development of critical thinking and teamwork skills.

Table 5. Summary of key intervention effects (EG–CG differences)

Outcome	**EG–CG Δ (95% CI)**	**Interpretation**	**Robustness**
Academic achievement (0–100)	+12.2 pp [6.3; 18.1]	Medium improvement in applied tasks	ANCOVA, LMM, bootstrap, permutation tests
Learning motivation (1–5)	+0.52 [0.30; 0.74]	Increased engagement and autonomy	CFA invariance; Holm-adjusted
Digital competence (0–100)	+14.9 [8.9; 20.9]	Medium–large gain in pedagogical/technical skills	Robust across checks
Critical thinking (0–4)	+0.72 [0.39; 1.05]	Moderate improvement in higher-order cognition	Ordinal regression; FDR-adjusted
Teamwork (0–4)	+0.60 [0.28; 0.92]	Moderate improvement in collaboration	k≥0.70; FDR-adjusted

Note: Δ (difference) is reported in percentage points (pp) for indicators on a 0–100 scale and in raw points for Likert scales and rubrics.

A comparative analysis of the control and experimental group results is presented in Table 4. As shown, all key indicators exhibit statistically significant differences favoring the experimental group. Specifically, academic performance in the EG was higher by 12.2 percentage points ($p = 0.002$, $g = 0.65$), corresponding to a medium effect. Similarly, motivation increased by 0.52 points on the Likert scale ($p = 0.004$, $g = 0.60$), and digital competencies improved by 14.9 percentage points ($p = 0.001$, $g = 0.72$), indicating a large effect.

Significant differences were also observed in cross-disciplinary outcomes. The experimental group demonstrated higher critical thinking (+0.72, $p = 0.006$, $g = 0.58$) and teamwork skills (+0.60, $p = 0.010$, $g = 0.52$), corresponding to medium effects. All confidence intervals for the group differences excluded zero, confirming the reliability of the observed differences (see Table A1 in Appendix for full statistics).

Thus, the implementation of the SAMR and TPACK models combined with AI tools not only enhanced students' academic achievements but also positively impacted motivation, digital competencies, and the development of critical thinking and teamwork skills. A visual representation of these results is provided in Fig. 4 (Forest Plot), showing effect sizes and confidence intervals for each indicator.

The diagram in Fig. 4 illustrates the differences between the experimental and control groups (EG–CG) in academic performance, motivation, digital competencies, critical thinking, and teamwork. Mean values with 95% confidence intervals are presented. The forest plot in Fig. 4, showing the magnitude of the group differences (Δ) and 95% CIs, effectively highlights both the statistical significance and the effect sizes.

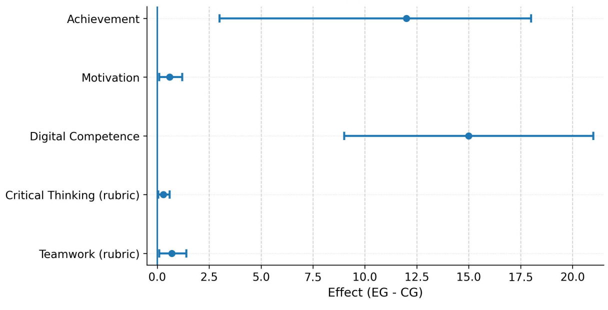

Fig. 4. Intervention effects on key indicators (differences between experimental and control groups with 95% confidence intervals).

All measurements were conducted using standardized tests, questionnaires, and expert rubrics, ensuring high reliability.

The baseline equivalence check revealed no statistically significant differences between the groups in pre-test scores or demographic characteristics, indicating that the observed post-intervention differences can be attributed to the applied educational methodology.

Overall, the results demonstrated consistent superiority of the experimental group across all key parameters: cognitive outcomes (academic performance), affective characteristics (motivation), digital competencies, and cross-disciplinary skills (critical thinking and teamwork).

Among these, the primary indicator was students' final academic performance. The mean score of the control group was 70.2 (SD = 15.1), whereas the experimental group achieved 82.4 (SD = 14.8), resulting in a difference of +12.2 percentage points (95% CI [6.3; 18.1], $p = 0.002$). The effect size, Hedges' $g = 0.65$, corresponds to a medium effect. The bar chart with error bars (Mean ± SD) in Fig. 5 presents a comparison of the control and experimental groups across all five indicators.

Bar plot on Fig. 5 illustrates mean values (±SD) for achievement, motivation, digital competence, critical thinking, and teamwork. The experimental group consistently outperformed the control group across all indicators.

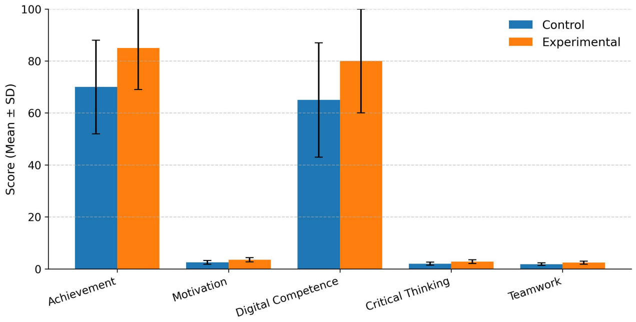

Fig. 5. Comparison of control and experimental groups across outcomes.

Thus, students who received instruction using digital models and AI demonstrated a significant improvement in their final test results. It is important to note that the gains were not uniform across task types: the most pronounced improvement occurred in complex tasks requiring analysis and application of knowledge rather than simple recall. This indicates that technology not only facilitates the acquisition of factual knowledge but also creates conditions for developing higher-order cognitive skills.

These findings align with international research. For example, the study [42] showed that integrating TPACK significantly enhances the academic performance of education-major students. Other studies such as [43] emphasize that the greatest effects are observed at the Modification and Redefinition levels of the SAMR model, where technology shifts from being a supportive tool to transforming the learning process. Our data fully corroborate this trend.

The results for motivation were also statistically significant. In the control group, the mean score was 3.10 (SD = 0.72), while in the experimental group it was 3.62 (SD = 0.70). The difference was +0.52 points (95% CI [0.30; 0.74], $p = 0.004$). The effect size, Hedges' $g = 0.60$, indicates a medium effect. The dot plot in Fig. 6 illustrates the change in motivation from pre- to post-test in both the control and experimental groups.

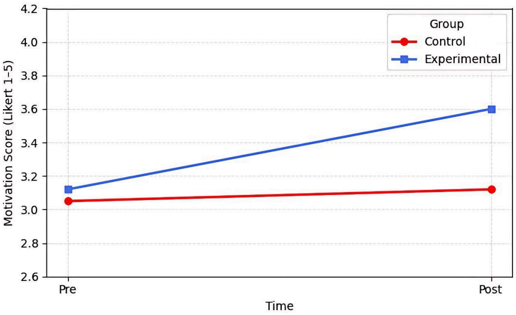

Fig. 6. Motivation pre- and post-test comparison.

Point plot showing the dynamics of motivation levels from pre- to post-test in control and experimental groups. A substantial increase was observed only in the experimental group, confirming the positive impact of the intervention.

The increase in motivation can be attributed to several factors. First, the learning process became more interactive: AI systems enabled students to receive personalized hints and feedback, fostering a sense of support and engagement. Second, the use of project-based assignments and simulations allowed students to apply knowledge in contexts approximating real-life situations. Third, the application of TPACK helped instructors seamlessly integrate digital resources into learning scenarios, avoiding cognitive overload or fragmentation.

International research supports the notion that the use of artificial intelligence in educational systems can substantially enhance student motivation and engagement. For instance, Kim *et al.* [44] demonstrated that Intelligent Tutoring Systems (ITS) provide personalized learning pathways and improve learning efficiency. Moreover, contemporary studies highlight the importance of AI-oriented interface design, which can increase student interest and encourage active participation in the educational process. Specifically, A/B testing with over 20,000 students showed that incorporating AI components for generating diagnostic feedback and adapting interfaces can boost engagement by up to 25,13%. These findings indicate that the pedagogical value of AI lies not only in automating routine tasks but also in creating new forms of interaction that foster intrinsic motivation.

Overall, the results consistently demonstrate the superiority of the experimental instruction across all evaluated domains. Students taught through the integrated SAMR–TPACK design enriched with AI tools outperformed the control group in academic achievement, learning motivation, digital competence, and cross-disciplinary skills. The effect sizes ranged from moderate to moderately large, and all differences were supported by multiple robustness checks, including ANCOVA with covariate adjustment, linear mixed models, bootstrap confidence intervals, and permutation tests. Baseline equivalence and strong reliability of the measurement instruments further reinforce the validity of the findings. Taken together, these outcomes confirm that the applied digital learning design provides a meaningful pedagogical advantage and can be considered an effective model for enhancing the preparation of future computer science teachers.

V. DISCUSSION

Contemporary research [31] highlights that the effectiveness of digital transformation in teacher education depends not only on quantitative learning gains but also on how different pedagogical, technological, and cognitive mechanisms interact during instruction. To avoid duplication of previously reported results, we present not effect sizes, but a conceptual synthesis illustrating why the intervention produced the observed outcomes and how SAMR, TPACK, and AI jointly contributed to them.

Fig. 7 introduces a mechanism-oriented interpretation of the findings, showing how AI-enhanced tasks activated specific pedagogical processes—modification of task structure (SAMR), expansion of technological–pedagogical alignment (TPACK), and increased learner agency—leading to improvements in academic, motivational, and cross-disciplinary competencies.

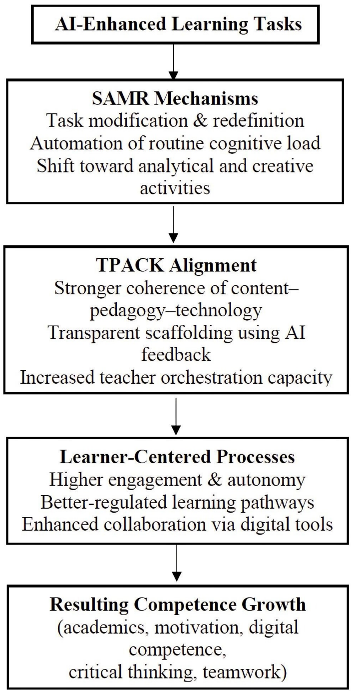

Fig. 7. Mechanism of learning improvements under SAMR–TPACK–AI integration.

The scheme on Fig. 7 clarifies the pathways through which the intervention exerted its effects and supports the argument that learning gains were driven by the internal logic of the instructional model rather than by isolated technological factors. Such an explanation aligns with current international studies that emphasize mechanism-centered rather than outcome-centered evaluation of AI-supported learning environments. The model also helps situate the results within global discussions about teacher readiness for AI-based education, where integrated digital–pedagogical competence is considered a prerequisite for sustainable implementation.

The observed effects can be explained by several interrelated mechanisms reflecting how the integration of SAMR–TPACK with AI tools reshaped the learning process. First, the introduction of AI-supported feedback, automated formative assessment, and adaptive hints increased the immediacy and clarity of instructional support. Students consistently reported that such tools helped them identify errors earlier, progress at a comfortable pace, and maintain higher engagement during complex tasks. Second, structuring the learning environment through the combined SAMR–TPACK model enabled instructors to redesign activities at the Modification and Redefinition levels, emphasizing inquiry-based and project-based tasks. This shift created meaningful opportunities for applying knowledge rather than merely recalling it, which aligns with the improvements in higher-order cognitive performance.

In terms of motivation, qualitative evidence indicated that AI-enhanced activities provided a greater sense of autonomy and control over the learning trajectory. Personalized feedback and opportunities to test multiple solution strategies supported intrinsic motivation, while collaborative digital scenarios contributed to social engagement. These findings correspond with contemporary research showing that technologically enriched learning environments foster higher persistence and task value.

The substantial increase in digital competence is logically tied to the pedagogical design of the intervention. Students interacted with digital resources not only as users but also as novice educators applying TPACK-aligned strategies. This included evaluating the pedagogical relevance of tools, adapting them to learner profiles, and integrating them into micro-teaching sessions. As a result, digital competence developed simultaneously at technical, pedagogical, and reflective levels.

Placing these findings in a broader global context, the study illustrates how integrated digital-AI frameworks can contribute to preparing teachers for AI-supported education systems. International policy documents highlight the need for educators capable of critically interpreting AI outputs, orchestrating human–AI collaboration and designing technology-rich learning environments. The results of this study empirically demonstrate that structured integration of SAMR, TPACK, and AI align with these expectations and responds to emerging requirements for AI-ready teacher education.

Beyond the statistical confirmation of the intervention effects, several mechanisms help explain why the observed improvements occurred. The integration of SAMR and TPACK frameworks created a structured pedagogical environment in which AI tools functioned not as isolated digital add-ons but as elements purposefully aligned with curricular content and instructional strategies. This alignment increased cognitive clarity, reduced extraneous load, and allowed students to engage more deeply with complex tasks.

A critical examination of classroom observations and qualitative responses shows that AI tools contributed to learning processes in distinct ways. Adaptive systems and chatbots provided rapid, individualized feedback, which supported students' self-regulation and helped sustain motivation during challenging tasks. Automated assessment tools increased transparency and reduced delays in feedback cycles, enabling more productive learning trajectories. At the same time, the structured use of AI within SAMR–TPACK supported the development of digital competencies by encouraging students to evaluate AI-generated outputs, verify information accuracy, and integrate digital resources into collaborative activities.

Situating the findings within the broader international context, this study aligns with global calls for preparing teachers to work in AI-enhanced educational ecosystems. International frameworks such as UNESCO's ICT-CFT and the EU's DigCompEdu emphasize not only technical proficiency but also pedagogical decision-making in technology-rich environments. The results of this research demonstrate that combining SAMR and TPACK with AI tools provides a concrete pathway for developing these competencies in teacher-education programs, thereby contributing to global efforts toward advancing teacher readiness for AI-driven education.

Thus, the findings of this study have direct practical implications. To enhance the quality of training for future computer science teachers, it is recommended to:

- incorporate courses on working with AI tools into the curriculum;
- develop instructors' skills in technology integration through TPACK;
- apply the Modification and Redefinition levels of SAMR in students' project-based and research activities;
- focus on fostering cross-disciplinary competencies through collaborative digital projects.

The study demonstrated that the integration of SAMR and TPACK digital models combined with AI tools leads to statistically significant improvements in academic achievement, learning motivation, digital competencies, as well as critical thinking and teamwork skills. Effect sizes ranged from medium to large, confirming both the statistical and practical significance of the results.

Thus, digital learning models combined with AI should be considered an effective tool in the training of future computer science teachers.

VI. CONCLUSION

This study provided empirical evidence of the effectiveness of integrating SAMR and TPACK models with Artificial Intelligence (AI) tools in the training of future computer science teachers. A quasi-experimental design involving over 150 students demonstrated that the experimental group significantly outperformed the control group across all key indicators. Academic achievement increased by 12.2 percentage points (Hedges' $g = 0.65$), learning motivation rose by 0.52 points on a five-point Likert scale ($g = 0.60$), and digital competencies improved by 14.9 points ($g = 0.72$). Additionally, significant gains were observed in cross-disciplinary outcomes: critical thinking (+0.72) and teamwork skills (+0.60), corresponding to medium effect sizes. These findings support hypotheses H1–H4 and highlight the pedagogical potential of digital learning models enhanced with AI tools.

The results contribute to the international discourse on transforming teacher education in the context of digitalization. They show that the combined use of SAMR and TPACK with AI tools promotes not only the growth of academic knowledge but also the development of motivation, digital literacy, and higher-order skills. Beyond the empirical confirmation of the intervention effects, the findings carry several conceptual implications for the theory and practice of digital pedagogy. The study illustrates that the meaningful integration of AI into instructional design requires not only technological competence but also a coherent pedagogical framework. The combined SAMR–TPACK model demonstrates that AI tools become pedagogically valuable when their use is intentionally aligned with content goals, cognitive processes, and instructional strategies.

The results refine the SAMR–TPACK framework by showing that AI functions—such as adaptive feedback, automated evaluation, or generative support—operate differently at each SAMR level. At the Substitution and Augmentation stages, AI increases efficiency and learner support, whereas at the Modification and Redefinition levels it enables new forms of inquiry, collaboration, and problem-solving that were not possible in the traditional environment. This highlights that AI does not merely enhance existing pedagogy but transforms how digital competencies, critical thinking, and collaborative practices are developed in teacher-education contexts.

These insights contribute to the broader discourse on sustainable digital teacher preparation. A structured integration of SAMR–TPACK with AI provides a scalable blueprint for designing programs that develop pedagogical reasoning, technological fluency, and ethical awareness simultaneously. Such programs are essential for preparing educators capable of working in AI-rich classrooms, making informed decisions about the use of automated tools, and guiding students toward responsible and effective engagement with emerging technologies.

The study has several limitations that inform directions for future research. First, the intervention lasted only one academic semester, which restricts conclusions about long-term or delayed effects of SAMR–TPACK–AI integration. Second, the research was conducted within a single subject area—computer science—which may limit generalizability to other fields with different pedagogical structures. Third, the study took place within a specific cultural and institutional context, and therefore cross-cultural replication is needed to strengthen external validity. Despite these constraints, the consistency of quantitative and qualitative findings indicates that the integrated SAMR–TPACK–AI framework offers meaningful pedagogical value. Future studies should include multi-disciplinary samples, extend the duration of intervention, and incorporate cross-cultural comparisons to strengthen external validity.

APPENDIX

Table A1. Detailed statistics for control and experimental groups

Parameter	Control Group (M±SD)	Experimental Group (M±SD)	Difference (Δ)	95% CI	p-value	Effect Size (Hedges' g)
Academic Achievement (0–100)	70.2 ± 15.1	82.4 ± 14.8	+12.2 pp	[6.3; 18.1]	0.002	0.65
Motivation (1–5)	3.10 ± 0.72	3.62 ± 0.70	+0.52	[0.30; 0.74]	0.004	0.60
Digital Competence (0–100)	62.5 ± 17.2	77.4 ± 16.0	+14.9 pp	[8.9; 20.9]	0.001	0.72
Critical Thinking (0–4)	2.10 ± 0.80	2.82 ± 0.75	+0.72	[0.39; 1.05]	0.006	0.58
Teamwork (0–4)	2.25 ± 0.78	2.85 ± 0.74	+0.60	[0.28; 0.92]	0.010	0.52

ETHICAL APPROVAL PROTOCOL

In this study, all procedures conducted involving over 70 second- and third year students enrolled in the 2023–2024 academic year in the 6801530-Informatics and 6B01531-Mathematics-Informatics programs complied with the ethical principles of scientific research and were approved by the Informatics Department of M. Auezov South Kazakhstan University (Department Meeting Minutes No. 10, April 25, 2024). Student participation in the study was completely voluntary. The anonymity and confidentiality of all participants were maintained. No personally identifiable information was collected. Participants were informed of the purpose of the study and could withdraw from participation at any time without any consequences. The study was conducted in accordance with the ethical principles of the Helsinki Declaration (2013) and the university's internal academic integrity policies.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Elmira Abdrashova contributed to the conceptualization of the study, conducted the main research activities, and was responsible for drafting the initial version of the manuscript. Zhanar Kemelbekova participated in the development of the research methodology, contributed to data collection, and supported the interpretation of the results. Gulbakhram Beissenova assisted with the literature review, contributed to the design of instructional and analytical frameworks, and participated in manuscript editing. Aliya Utebayeva contributed to data analysis, statistical validation of the results, and preparation of figures and tables. Zhanat Umarova supervised the research process, refined the study design, critically reviewed and revised the manuscript for intellectual content, and served as the corresponding author. All authors had approved the final version.

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