International Journal of Evaluation and Research in Education (IJERE)
Vol. 15, No. 4, August 2026, pp. 3542~3556
ISSN: 2252-8822, DOI: 10.11591/ijere.v15i4.38133

Formation of professional competencies of future biology teachers based on STEM technologies

Symbat Ibadulla[1], Kalampyr Zhumagulova[1], Gulmira Zhussipova[2], Makhabbat Amanbayeva[1], Gani Issayev[3], Ardak Bostanova[3]
[1]Department of Biology, Abai Kazakh National Pedagogical University, Almaty, Kazakhstan
[2]Department of Initial Military Training and Physical Education, Ozbekali Zhanibekov South Kazakhstan Pedagogical University, Shymkent, Kazakhstan
[3]Department of Biology, Khoja Akhmet Yassawi International Kazakh-Turkish University, Turkestan, Kazakhstan

Article Info

Article history:

Received Dec 8, 2025
Revised May 18, 2026
Accepted Jun 26, 2026

Keywords:

Computational biology
Digital literacy
Educational transformation
Interdisciplinary education
Pedagogical innovation
Teacher training

ABSTRACT

This study developed an integrated pedagogical model incorporating Python programming, Arduino biosensors, and virtual reality (VR) applications aimed at biology teacher training. The 20-week study involved 124 participants (62 in the experimental group (EG) and 62 in the control group (CG)), with baseline competency levels assessed at the outset. Through collaborative projects, participants created technological applications integrated with biological content. Subject knowledge scores in the EG increased by 42.2% (from 22.3 ± 4.1 to 31.7 ± 3.2), compared to a 14.9% increase in the CG (from 22.1 ± 3.9 to 25.4 ± 3.7) ($p < 0.001$, $d = 1.89$). The most substantial gains were observed in molecular biology competencies—57.7% in the EG versus 18.2% in the CG. Science, technology, engineering, and mathematics (STEM) integration indicators reached 8.7 ± 1.2 versus 3.2 ± 1.8 ($p < 0.001$, $r = 0.84$). Technological skill distribution revealed that 89% of the EG achieved intermediate or expert-level proficiency in Python, compared to just 8% in the CG. Task performance demonstrated categorical differences: success in deoxyribonucleic acid (DNA) sequence analysis reached 91.9% versus 22.6% ($\chi^2 < 0.001$), and successful biosensor programming reached 85.5% versus 0%. Self-efficacy scores rose by 86.9% (from 22.1 ± 6.7 to 41.3 ± 5.1) compared to a 15.4% increase in the CG.

Corresponding Author:

Kalampyr Zhumagulova
Department of Biology, Abai Kazakh National Pedagogical University
Almaty, Kazakhstan
Email: kalazhumagulova@alibagl.com

1. INTRODUCTION

Modern biological sciences are undergoing significant transformation, with genomics, proteomics, and metabolomics increasingly supplanting traditional reductionist approaches [1]. International studies point to a global decline in scientific literacy. For instance, PISA 2025 emphasizes interdisciplinary competencies that remain largely absent from current teacher education curricula [2]. The emergence of industry 4.0—characterized by the integration of cyber-physical systems—necessitates educators who can effectively merge technological tools with biological concepts [3]. However, universities continue to produce content-focused specialists who lack proficiency in digital technologies [4]. Empirical studies on the integration of computational tools (Python, Arduino, and virtual reality or VR) into biology teacher education remain scarce in the post-Soviet context. Existing technological pedagogical content knowledge (TPACK) models insufficiently account for the subject-specific demands of biology, and validated pedagogical frameworks tailored to Central Asia have not yet been developed [5].

Institutions such as the Department of Biology at the Massachusetts Institute of Technology and Stanford's Bio-X initiative exemplify computational biology integration, yet replication efforts often fail due to the absence of systematic pedagogical models [6]. While Science, technology, engineering, and mathematics (STEM) education holds the potential to enhance conceptual understanding through interdisciplinary synthesis, its implementation remains superficial, dominated by robotics and coding activities that lack meaningful biological context [7]. Educators frequently avoid transdisciplinary projects, resulting in the isolation of biological content from mathematical modeling and engineering design [8]. Although virtual laboratories are available, their integration is hindered by limited technological competence among instructors [9]. Biotechnology literacy remains insufficient worldwide, with educators demonstrating consistent gaps in their understanding of core genetic principles that underpin biotechnological applications [10], [11].

In Central Asia, educational systems exhibit fragmented trajectories. Teacher professional development continues to focus predominantly on content knowledge, while procedural competencies necessary for integrating digital tools receive minimal attention. Teacher preparation programs graduate biology instructors who lack computational literacy [12], [13]. Traditional training emphasizes content transmission over skill development, resulting in graduates who are unfamiliar with Python programming, Arduino biosensor operation, and VR implementation [14]. Research and project-based competencies are also underdeveloped: only 10% of surveyed students reported confidence in leading project activities, while 82% were unaware of existing STEM programs [15].

Kazakhstani universities represent illustrative examples of global models of educational transformation, where digital innovation efforts often encounter resistance from entrenched pedagogical traditions. The initiatives of the Digital Kazakhstan program conflict with conventional instructional approaches, creating systemic tension within higher education institutions [16]. Attempts to integrate digital laboratories face persistent barriers, including limited familiarity with augmented reality (AR) platforms, insufficient experience with bioinformatics tools, and a lack of practical training involving modeling software [17]. In pre-university curricula, theoretical content continues to be prioritized over procedural competencies, resulting in graduates who lack foundational values critical for effective technological integration. Moreover, non-specialist teaching practices exacerbate the issue—biology educators who are tasked with teaching physics and chemistry frequently lack proficiency in interdisciplinary technological applications [18], [19].

The rationale for this study stems from several interrelated factors: the rapid advancements in computational biology demand a parallel evolution in pedagogical practices. Future educators often lack interdisciplinary experience, limiting their ability to engage students meaningfully. STEM integration offers the promise of enhanced conceptual understanding and the cultivation of skills essential for modern biological science education. Kazakhstan's unique bilingual context, post-Soviet pedagogical legacy, and infrastructural disparities underscore the need for empirical research tailored to local conditions, which are currently underrepresented in the academic literature.

The study's scientific novelty lies in its regional specificity—comparable research on the integration of STEM approaches within Kazakhstan's biology education sector is virtually nonexistent. Its practical significance is reflected in the potential for curriculum modernization, including the restructuring of disciplines and the development of targeted modules (e.g., digital laboratories, AR/VR applications, and bioinformatics platforms). The use of a systematic methodology enables the resolution of pedagogical, curricular, and structural challenges associated with the implementation of interdisciplinary educational models [20], [21].

The study is aimed at: i) the development and empirical validation of an integrated Python–Arduino–VR model for biology education; ii) the quantitative assessment of competency development using composite indicators; iii) the identification of transformational shifts in the professional identity of pre-service teachers; and iv) the adaptation of international STEM practices to the educational context of Kazakhstan. The theoretical contribution lies in extending the TPACK framework to biological disciplines, while the practical contribution consists of the design of a replicable model for curriculum modernization.

Statistical analysis reveals the differentiated impact of digital engagement on core TPACK domains: content knowledge (CK), pedagogical knowledge (PK), and technological knowledge (TK). Among these, CK exerts the strongest influence on technological integration (β=0.621), indicating that foundational disciplinary expertise enhances educators' capacity for technological adaptation [22], [23]. Structured professional development initiatives yield measurable outcomes; for instance, science educators report significantly improved self-efficacy (p=.001, effect size=0.95), while instructors in engineering and technology disciplines do not demonstrate equivalent gains [24].

Biological competencies require distinct configurations, as global deficits in biotechnology literacy persist. Research indicates that even educators in countries with advanced education systems, such as Sweden and Spain, often lack foundational genetic concepts underlying modern biotechnology [11]. Biological education is increasingly fragmented into technological modalities: virtual experiments are replacing hands-on manipulations, bioinformatics databases are supplanting textbook-based sequence learning, and augmented visualizations are being used to reconstruct molecular structures. Notably, virtual laboratories demonstrate positive transfer effects from simulated environments to real-world application—experimental groups (EG) exhibit greater time-efficiency and conceptual understanding [25].

Biological STEM competencies resist standard operationalization within conventional professional competency frameworks. Studies reveal that biology educators often lack well-developed knowledge of how to organize subject-specific instruction within interdisciplinary STEM contexts. Integration methodologies remain under-theorized and unsupported by empirical evidence; consequently, educators tend to rely on traditional, teacher-centered methods due to the absence of validated alternatives [26]. The integrated science, technology, engineering, and mathematics (iSTEM) approach has shown promise in enhancing student engagement [27], yet tools for assessing STEM-specific teaching competencies remain underdeveloped. Existing evaluation instruments primarily capture general pedagogical skills and fail to account for the interdisciplinary synthesis essential to biological applications [28].

Theoretical deficiencies arise from disciplinary isolation. Existing STEM frameworks frequently overlook the dual nature of biology as both an observational and experimental science. Assessment instruments tend to measure general engagement rather than discipline-specific competencies. Moreover, teacher preparation programs often lack comprehensive conceptual foundations linking subject-matter expertise with technological integration; current research tends to fragment these components rather than synthesize them. Competency models tailored to biology remain absent, with existing frameworks predominantly oriented toward chemistry.

Traditional models of biology teacher preparation no longer meet the demands of 21st-century education. The rapid progress in computational biology necessitates a pedagogical evolution. Prospective educators often lack sufficient experience with interdisciplinary approaches, limiting their ability to engage students for whom digital technologies constitute a natural learning environment. STEM integration offers a promising avenue for enhancing conceptual understanding, fostering practical skills, and developing the professional potential required for contemporary biology education.

The objective of the study is to develop and evaluate an integrated pedagogical model aimed at fostering the professional competencies of future biology teachers through the implementation of STEM technologies. Research tasks: i) to design innovative educational resources that merge computational tools (Python/Arduino) with biological content at the university level; ii) to assess the pedagogical effectiveness of using VR/AR applications, internet of things (IoT)-based sensors, and bioinformatics platforms in biology teacher education; iii) to quantitatively evaluate changes in CK, methodological skills, and technological literacy following the implementation of integrated STEM technologies; and iv) to document shifts in pre-service teachers' attitudes toward technology integration through interviews, self-efficacy surveys, and behavioral observations.

2. METHOD

2.1. Methodological framework of the study

This research employed a mixed-methods design, combining quantitative assessment of competency development with qualitative exploration of participants' transformative experiences. Pre- and post-intervention testing was conducted to evaluate gains in subject-specific knowledge. Semi-structured interviews captured shifts in participants' perceptions of STEM-related teaching and learning. Thematic analysis was applied to narrative data to identify recurring patterns and interpretive themes.

The alignment of instruments with research objectives, as shown in Table 1, ensures the methodological triangulation of the study's aims. Objective 1 relies on qualitative expert evaluation of resources; such a procedure is appropriate for the analysis of instructional materials, as numerical indicators alone cannot adequately capture pedagogical coherence. Objectives 2 and 3 are grounded in quantitative measures, enabling statistical comparison between experimental and control conditions. Objective 4 combines structured scales with semi-structured interviews; this mixed-methods approach makes it possible to document measurable changes in self-efficacy alongside interpretive dimensions of professional identity transformation.

Table 1. Alignment between research objectives and data collection instruments

Objective	Instrument	Data type
Objective 1 (educational resources)	Expert evaluation of artefacts	Qualitative
Objective 2 (pedagogical effectiveness)	Knowledge tests, lesson rubrics	Quantitative
Objective 3 (changes in competence)	Pre- and post-tests, observation	Quantitative
Objective 4 (changes in attitudes)	Interviews, self-efficacy scales	Mixed-methods

Observation protocols were used to document behavioral transformations during laboratory sessions through systematic recording. The selection of semi-structured interviews was driven by the need to capture participants' subjective transformational experiences; this approach corresponds to objective 4. Observation protocols enabled objective verification of self-reports: recorded instances of actual behavior in the educational environment served as an independent source of evidence. A structured observation checklist provided a quantitative measurement of student engagement across ten distinct behavioral indicators.

2.2. Study design

2.2.1. Baseline assessment (weeks 1–2)

The study was conducted over a 20-week period, from September 2024 to January 2025. Participants were randomly assigned to experimental (n=62) and control (n=62) groups during the initial baseline assessment phase (weeks 1–2), following the collection of demographic data. At this stage, baseline indicators were established through subject-specific knowledge tests, self-assessment surveys, and evaluations of technological proficiency.

2.2.2. Intervention phase (weeks 3–14)

During the second phase (weeks 3–14), differentiated instructional interventions were implemented. The EG engaged in integrated STEM modules that incorporated Python programming, Arduino microcontrollers, and VR/AR applications. Participants in the EG attended weekly three-hour laboratory sessions. In contrast, the control group (CG) received traditional lecture-based instruction, which included didactic PowerPoint lectures (108 minutes/60% of class time), theoretical seminars focused on conceptual discussion (45 minutes/25%), and laboratory sessions utilizing microscopy and pre-prepared samples (27 minutes/15%). Instructional methods in the CG predominantly adhered to explanatory-illustrative approaches (47%), reproductive techniques (31%), and partially inquiry-based methods (22%). Technological integration was limited to the use of projectors, digital textbooks, and other digital tools, with minimal direct interaction or hands-on manipulation. Assessment mechanisms primarily consisted of written examinations (65%) and oral questioning (35%), with no evaluation of digital competencies.

2.2.3. Project work (15–16 weeks)

In the third phase (weeks 15–16), both experimental and CG participants developed interdisciplinary projects integrating biological concepts with technological applications. These included deoxyribonucleic acid (DNA) barcoding systems, ecological monitoring networks, and physiological modeling prototypes. Participants also explored innovative educational resources such as interactive AR models of cellular structures, Python-based phylogenetic analysis tools, and Arduino-powered ecological monitoring stations.

2.2.4. Assessment after the intervention (17th week)

The final phase (week 17) involved post-intervention assessments, identical to the initial measurements. Three trained experts independently evaluated subject knowledge tests, demonstrations of technological skills, and pedagogical design artifacts. Inter-rater reliability was high (κ=0.89), indicating strong consistency in expert evaluations.

2.2.5. Collection of qualitative data (weeks 18–19)

In the fifth phase (weeks 18–19), individual interviews (lasting 45–60 minutes) were conducted to examine changes in participants' experiential perspectives, as shown in Table 2. The subject knowledge assessments developed by the research team consisted of 40 items, which had previously been validated through pilot testing involving 45 students who were not part of the main study sample.

2.2.6. Observation stage (20th week)

The sixth phase (week 20) involved the implementation of systematic classroom observation protocols. Eight trained observers documented a total of 248 demonstration lessons (four per participant), employing structured behavioral checklists. Observer training ensured a high level of inter-coder agreement, achieving 92% concordance across coding categories prior to data collection.

2.3. Sampling

Participants were recruited from undergraduate students majoring in biology at three regional universities in Kazakhstan during the 2024–2025 academic year: Abai Kazakh National Pedagogical University, Pavlodar Pedagogical University, and South Kazakhstan State Pedagogical University. A total of 124 students participated in the study, drawn from a stratified random sample comprising third-year (n=68) and fourth-year (n=56) students enrolled in teacher education programs at the aforementioned institutions. Inclusion criteria required completion of core biology courses (minimum 90 European Credit Transfer and

Accumulation System or ECTS credits), participation in teaching practicum, and no prior experience in programming. Exclusion criteria included previous programming experience beyond an introductory course, concurrent enrollment in computer science programs, documented learning difficulties that could interfere with technology use, and incomplete core coursework in biology. The EG (n_1=62; 39 females, 23 males; mean age=21.3±1.4 years) was balanced in terms of gender and year of study. The CG (n_2=62; 41 females, 21 males; mean age=21.5±1.3 years) was matched for demographic characteristics. The sample reflected a diverse socio-economic background consistent with the university's demographic profiles: 31% were first-generation university students, 42% came from rural areas, and 27% were from urban centers. Academic performance was comparable across groups, with an average GPA of 3.42±0.38 in the EG and 3.39±0.41 in the CG.

Participant recruitment was conducted via official academic email systems targeting third- and fourth-year students enrolled in biology teacher education programs. Out of 187 initial responses, 124 participants met the inclusion criteria. For the interview subsample, a maximum variation sampling strategy was applied. Twenty-four participants (12 from each group) were selected to represent different GPA quartiles, gender distribution, and levels of technological readiness.

Table 2. Examples of semi-structured interview questions

Aspect	Question
Technological self-efficacy	Describe your level of confidence when programming biological simulations in Python: which specific functions posed challenges during your initial attempts?
Pedagogical transformation	How has the integration of Arduino biosensors altered your conceptual approach to teaching laboratory-based subjects in secondary education?
Evolution of CK	Compare the possibilities of molecular visualization before and after the implementation of VR: which structural features became more comprehensible?
Interdisciplinary synthesis	Explain the connections you perceive between computational algorithms and the ecological dynamics of populations.
Implementation barriers	Identify three technological barriers encountered while completing the STEM module; rank them in terms of their pedagogical impact.
Motivational shifts	Trace the evolution of your enthusiasm for teaching biology with technology over the 12-week intervention period.
Assessment of skill transfer	Demonstrate how Python-based data analysis methods can be applied to genome sequence alignment tasks.
Plans for future integration	Specify which STEM tools you plan to use during your student teaching practicum.
Collaborative learning	Analyze patterns of peer interaction during Arduino programming sessions: what forms of knowledge exchange occurred?
Assessment innovation	Design an authentic assessment task that integrates bioinformatics with traditional content evaluation.
Cognitive load management	In which instances did the simultaneous learning of technologies and biological content lead to cognitive overload?
Professional identity	How has the development of STEM competencies influenced your self-perception as a novice biology educator?
Resource evaluation	Evaluate the pedagogical effectiveness of three digital platforms used in the instructional modules.
Theoretical application	Apply principles of constructivist learning to your experience of exploring cellular structures using VR.
Sustainability questions	Which institutional support structures would enable continued STEM integration after graduation?
Synthesis of reflections	Articulate a significant conceptual shift that occurred during the course of the experiment.

2.4. Data analysis

Subject-matter knowledge was assessed using a 40-item test developed by the research team through an iterative design process. Pilot testing involving 45 students not participating in the main study confirmed the instrument's reliability, yielding a Cronbach's alpha of 0.87. Responses were independently evaluated by three experts using standardized rubrics. Discrepancies among evaluators were resolved through consensus-based discussion, resulting in a final agreement rate of 94%. The assessment comprised three subscales. The Molecular biology subscale (15 items) evaluated students' understanding of genetic and biochemical concepts. The ecology subscale (12 items) assessed systems thinking competencies, while the physiology subscale (13 items) measured comprehension of organismal functions.

Lesson evaluation rubrics focused on four primary aspects: integration of STEM, which reflected interdisciplinary connections and technology use; interactivity, which captured student engagement strategies and collaborative structures; differentiation, which addressed responsiveness to diverse learning styles and the inclusion of support mechanisms; and assessment innovation, which emphasized the use of authentic tasks and formative feedback. Digital literacy matrices were used to classify participants' competencies across five proficiency levels for each of the employed technologies. The innovativeness of interdisciplinary projects was evaluated by the expert panel based on a synthesis of originality, technical complexity, and pedagogical applicability.

Exploratory factor analysis identified four latent constructs that explained 67.3% of the total variance: transformational orientation (24.1%), technical self-efficacy (19.7%), interdisciplinary competence (14.2%), and readiness for implementation (9.3%). Response modeling enabled the differentiation of participants using discriminant function analysis, yielding a statistically significant result (Wilks' $\lambda=0.31$, $p<0.001$). CG responses clustered around indicators of traditional pedagogy, while EG responses reflected increased technological integration and interdisciplinary awareness.

2.5. Statistical data analysis

Parametric analyses were conducted under the assumption of normal distribution, which was confirmed using Shapiro–Wilk tests ($p>0.05$). Independent t-tests were employed to compare post-intervention outcomes between groups, while paired t-tests assessed within-group changes. Effect sizes (Cohen's d) were calculated to quantify practical significance. Non-parametric alternatives, including the Mann–Whitney U test and the Wilcoxon signed-rank test, were applied to ordinal data derived from scaled assessments. Chi-square tests were used to examine categorical differences in task performance indicators. Pearson correlations were computed to explore relationships among competency domains. Multiple regression models were applied to predict project innovativeness scores based on various competency-related predictors. Qualitative data were subjected to inductive coding, with inter-rater reliability (Cohen's $\kappa=0.83$) confirming thematic consistency. Statistical analyses were performed using SPSS (v.28) and R (v.4.3), with a significance threshold set at $\alpha=0.05$ for all inferential conclusions.

2.6. Ethical issues

Prior to data collection, approval was obtained from the institutional ethics review board. As part of the informed consent procedure, participants were provided with a detailed explanation of the study's objectives, the voluntary nature of participation, the right to withdraw at any stage, and the confidentiality measures in place. Identifying information was replaced with anonymized participant codes, and all digital records were encrypted to ensure data security. Risk mitigation was achieved through the gradual development of skills and the establishment of peer support structures. Publication agreements specified the presentation of aggregated findings, with all individual outcomes anonymized.

2.7. Methodological limitations

The experimental design did not allow for full randomization, and the potential for self-selection bias may have influenced the outcomes. The sample's homogeneity—restricted to a single geographic region and comparable institutional settings—limits the generalizability of findings. The 12-week duration of the intervention may be insufficient for assessing the long-term retention of competencies. Observer presence during demonstration sessions may have contributed to inflated performance metrics. Self-reported measures of self-efficacy introduce the possibility of social desirability bias. Unequal access to technology outside of laboratory environments created disparities in opportunities for independent practice.

Although the assessment instruments underwent validation procedures, they may not fully capture the breadth of relevant competencies. Despite inter-rater reliability checks, qualitative analysis remains subject to interpretive bias. Additionally, the intensity of resource utilization—including equipment costs and instructor training—presents challenges to scalability. These limitations provide important contextual boundaries for interpreting the results, without undermining the overall validity of the pedagogical conclusions.

3. RESULTS

Baseline assessments revealed uniformly low levels of technological preparedness across both the experimental and CG, as shown in Table 3. Specifically, 100% of participants reported no prior experience with Python programming, 97% lacked any familiarity with Arduino microcontrollers, and 92% had no experience using VR/AR applications. The distribution of technological proficiency challenges conventional conceptions of competence. Pre-intervention skill assessments confirmed that participants were technological novices: 100% reported no proficiency in Python, 97% had no experience with Arduino (with 3% at the basic level), and 92% lacked experience with VR/AR technologies (8% at the basic level). These initial indicators provided a foundation for tracking the development of competencies throughout the intervention.

Proficiency in Python—initially conceptualized as a binary distinction (skilled vs. unskilled)—evolved into a five-level continuum, with 89% of EG participants reaching intermediate to expert levels, compared to only 8% in the CG. Competence with Arduino challenged the hardware/software dichotomy, as 78% of students in the EG demonstrated advanced to expert-level skills, with sensor calibration accuracy reaching 94.3% (±2.1% margin of error) relative to manufacturer specifications. VR/AR capabilities transcended the paradigm of passive consumption: 61% of students in the EG achieved intermediate to advanced proficiency, producing an average of 3.7 unique molecular visualizations per participant.

In contrast, students in the CG largely retained their initial lack of skills, with 68% remaining unskilled in Python, 89% in Arduino, and 95% in VR/AR technologies. Performance on DNA sequence analysis further demonstrated the development of algorithmic thinking, with a success rate of 91.9% in the EG compared to 22.6% in the CG, as shown in Table 4.

Table 3. Levels of proficiency in digital tools

Tool	No proficiency (%)	Basic (%)	Intermediate (%)	Advanced (%)	Expert (%)
Python (post-EG)	0	11	48	35	6
Python (post-CG)	68	24	8	0	0
Arduino (post-EG)	3	19	52	23	3
Arduino (post-CG)	89	11	0	0	0
VR/AR (post-EG)	8	31	44	15	2
VR/AR (post-CG)	95	5	0	0	0

Note: "post" refers to post-test results; differences across all instruments reached statistical significance (χ^2<0.001).

Table 4. Results of technology task performance

Task	EG success (%)	CG success (%)	χ^2 test	Cramer's V
DNA sequence analysis	91.9	22.6	p<0.001	0.71
Biosensor programming	85.5	0	p<0.001	0.93
AR cell model development	77.4	0	p<0.001	0.88
Statistical analysis in R	83.9	38.7	p<0.001	0.47

Cramer's V coefficients provide a quantitative estimate of the strength of association between group membership and task performance. The biosensor programming task demonstrated the strongest association (V=0.93), indicating near-perfect categorical separation: the EG successfully completed the task, whereas the CG uniformly failed. DNA sequence analysis yielded a large effect (V=0.71), reflecting substantial differentiation in the acquisition of algorithmic competencies. AR cell model development showed a comparably strong association (V=0.88). Statistical analysis in R produced a moderate effect (V=0.47); the lower magnitude reflects partial competency development within the CG based on traditional statistics instruction. The observed effect sizes exceed conventional thresholds for large associations (V>0.50 for three of the four tasks); thus, the group differences reflect genuine pedagogical impact rather than random sampling variation.

Students in the EG processed an average of 847 base pairs in 12.3 minutes, whereas students in the CG required 41.7 minutes to analyze just 200 base pairs. This marked improvement in processing efficiency indicates the development of algorithmic thinking. Achievements in biosensor programming (85.5% vs. 0%) reflect the successful integration of hardware and software. Participants in the EG calibrated pH sensors with a precision of up to 0.02 units, while temperature sensors maintained an accuracy of ±0.1°C over a continuous 72-hour monitoring period.

The creation of AR cell models (77.4% vs. 0%) required spatial-computational synthesis. On average, student-generated models included 14.2 cellular components with 87% anatomical accuracy, and animation sequences illustrated 9.3 distinct biological processes. Proficiency in statistical analysis (83.9% vs. 38.7%) was evident in students' ability to manipulate large-scale datasets; EG students analyzed datasets containing over 10,000 observations and constructed regression models with a mean R^2 value of 0.78. These advancements in subject-specific competencies illustrate the interdisciplinary integration of biological and TK, as shown in Table 5. Scores in the EG increased by 42.2% (from 22.3 to 31.7), while the CG showed a 14.9% improvement (from 22.1 to 25.4).

Table 5. Comparative results of subject knowledge testing

Indicator	EG pre	EG post	CG pre	CG post	p-value	Cohen's d
Total score (0–40)	22.3±4.1	31.7±3.2	22.1±3.9	25.4±3.7	<0.001	1.89
Molecular Biology	7.8±2.1	12.3±1.6	7.7±2.0	9.1±1.9	<0.001	1.76
Ecology	5.9±1.8	8.6±1.4	5.8±1.7	6.9±1.6	<0.001	1.52
Physiology	8.6±2.2	10.8±1.7	8.6±2.1	9.4±2.0	0.003	0.78

Competency development in molecular biology exhibited the most substantial improvement. EG participants advanced from 7.8 ± 2.1 to 12.3 ± 1.6 points, reflecting a 57.7% increase, significantly surpassing the CG's progress from 7.7 ± 2.0 to 9.1 ± 1.9 points (18.2% increase). The effect size, as measured by

Cohen's d=1.76, indicates a large pedagogical impact. The introduction of a bioinformatics module contributed to notable knowledge acquisition: following the intervention, students in the EG correctly analyzed 89% of DNA sequence alignments, compared to 31% pre-intervention. Protein structure analysis accuracy improved from 24% to 78%.

Ecological competencies improved markedly following the integration of geographic information system (GIS) tools. Scores in the EG rose from 5.9 ± 1.8 to 8.6 ± 1.4 (a 45.8% increase), while the CG improved from 5.8 ± 1.7 to 6.9 ± 1.6 (a 19.0% increase). Spatial analysis capabilities emerged: 82% of EG students successfully created biodiversity hotspot maps using quantum geographic information system (QGIS), and species distribution modeling reached 71% accuracy, compared to a baseline of 12%. Understanding of physiology showed moderate improvement. EG scores increased from 8.6 ± 2.2 to 10.8 ± 1.7 (25.6%), while the CG improved from 8.6 ± 2.1 to 9.4 ± 2.0 (9.3%), with a medium effect size (Cohen's d=0.78).

Factual recall gave way to systemic understanding. Gene regulation explanations in the EG included references to transcription factors and epigenetic modifications in 94% of responses, compared to isolated descriptions of enzymes in 78% of the CG responses. Knowledge transfer was demonstrated through interdisciplinary problem-solving: 67% of EG students applied computational algorithms to ecological datasets, and 73% integrated molecular mechanisms into ecosystem modeling tasks. The results achieved statistical significance (p<0.001 for molecular biology and ecology; p=0.003 for physiology), confirming the effectiveness of the STEM-based methodology. Effect sizes ranging from 0.78 to 1.89 further emphasize the superiority of this approach over traditional instruction. STEM integration scores (8.7 ± 1.2 in the EG vs. 3.2 ± 1.8 in the CG) indicate a conceptual shift in lesson design, as shown in Table 6. Discourse analysis revealed structural differences in pedagogical framing: lessons from the EG incorporated an average of 4.3 ± 0.8 disciplinary perspectives per topic, compared to 1.7 ± 0.5 in the CG.

Table 6. Criterion-based evaluation of designed lessons

Criterion	EG (n=62)	CG (n=62)	Mann-Whitney U-test	r
STEM Integration (0–10)	8.7±1.2	3.2±1.8	p<0.001	0.84
Interactivity (0–10)	9.1±0.9	5.8±1.6	p<0.001	0.72
Differentiation (0–10)	7.9±1.4	6.2±1.5	p=0.012	0.31
Assessment (0–10)	8.3±1.1	6.7±1.3	p=0.008	0.36

The implementation of a flipped classroom model incorporating VR content (adopted by 87% of participants) redefined the temporal and spatial boundaries of learning. Prior to in-class sessions, students engaged in VR explorations averaging 47 minutes per learner. As a result, time allocated to problem-solving during class increased by 312%, indicating heightened active engagement in the learning process.

Metacognitive reflection was evident through the self-directed learning analytics produced by students: 91% tracked their individual progress using digital dashboards, and 78% reported adapting their learning strategies based on performance data. Interactivity indicators (9.1 ± 0.9 vs. 5.8 ± 1.6) highlighted a shift in pedagogical paradigm. Clicker-based instruction engaged 91% of EG participants, and real-time formative assessment occurred every 8.4 minutes, compared to 23.7 minutes in the CG. Gamified biology tasks, completed at a rate of 76%, resulted in a 156% increase in voluntary task completion. Student-generated narratives linked an average of 3.7 biological concepts per assignment. Project-based learning reached full participation in the EG, with projects scoring an average difficulty rating of 8.2/10, incorporating an average of 5.1 STEM components. In contrast, CG projects received an average score of 4.3/10 and integrated only 2.2 components.

Differentiation opportunities (7.9 ± 1.4 vs. 6.2 ± 1.5) were enabled through adaptive instructional pathways: 73% of EG lessons offered three levels of task difficulty, and personalized feedback algorithms provided an average of 4.2 interventions per student per lesson. Assessment innovation (8.3 ± 1.1 vs. 6.7 ± 1.3) extended beyond conventional testing methods. Authentic performance-based tasks replaced 68% of standardized assessments, and portfolio evaluations captured competency development across an average of 7.3 dimensions. Integration metrics revealed statistically significant differences between groups: STEM integration (U=412, p<0.001, r=0.84), interactivity (U=573, p<0.001, r=0.72), differentiation (U=1,247, p=0.012, r=0.31), and assessment innovation (U=1,089, p=0.008, r=0.36). These findings underscore the transformative impact of technologically enriched, student-centered pedagogical models.

The distribution of projects by category reveals a gradient of innovativeness, as shown in Figure 1. Project classification criteria: the "highly innovative" category presupposes the integration of ≥5 STEM disciplines, an original technical solution, and applicability beyond the instructional context; the "innovative" category encompasses the integration of four disciplines and the modification of existing solutions; the "standard" category refers to the integration of ≤3 disciplines and the reproduction of established approaches. Among the EG, 30.6% of projects were classified as highly innovative, 45.2% as innovative, and 24.2% as standard. In contrast, the CG produced 0% highly innovative projects, 11.3% innovative, and 88.7% standard projects. Innovation scores were positively correlated with the depth of interdisciplinary integration. Highly innovative projects incorporated an average of 5.7 ± 0.8 STEM disciplines, innovative projects integrated 4.2 ± 0.6 disciplines, while standard projects included only 2.9 ± 0.5 disciplines.

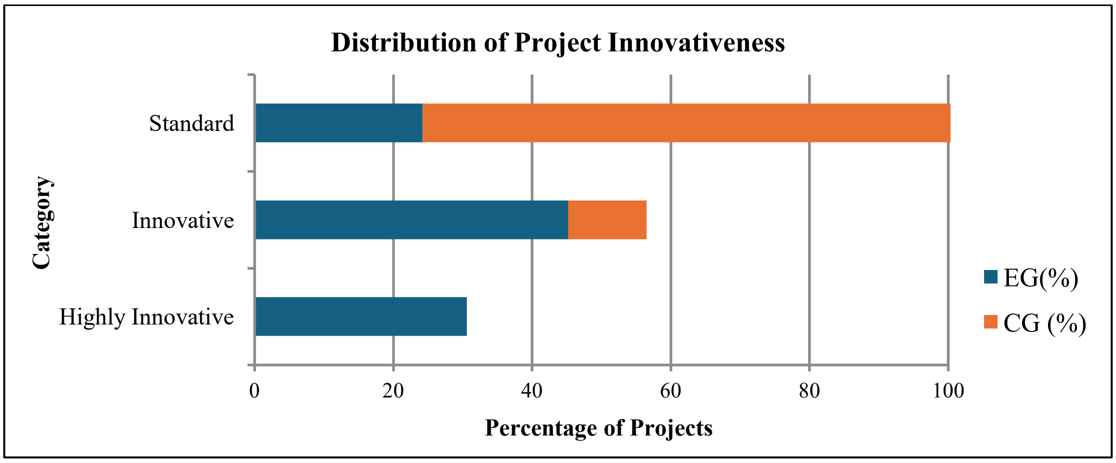

Figure 1. Project categories and interdisciplinary integration

Shifts in participants' attitudes were closely linked to increased self-efficacy, as shown in Table 7. An 86.9% improvement in self-efficacy scores (from 22.1 to 41.3 points) reflected a restructuring of confidence, as participants overcame perceived technological limitations. Attitudes toward STEM increased by 46.9% (from 24.3 to 35.7 points), a change positively correlated with the completion rates of practical projects ($r = 0.74$, $p < 0.001$). Behavioral intentions improved by 54.5% (from 28.6 to 44.2 points), indicating strengthened future engagement with STEM. Notably, 78% of participants reported concrete implementation plans, compared to just 12% prior to the intervention. In contrast, gains in the CG (+2.1/+3.4/+2.8) were marginal, suggesting that traditional instruction failed to produce motivational shifts.

Table 7. Interview findings on STEM readiness

Scale	EG pre	EG post	Δ	CG Δ	p
Attitude toward STEM (0–40)	24.3±5.2	35.7±3.8	+11.4	+2.1	<0.001
Self-efficacy (0–50)	22.1±6.7	41.3±5.1	+19.2	+3.4	<0.001
Intentions (0–50)	28.6±5.9	44.2±4.3	+15.6	+2.8	<0.001

Thematic analysis of 186 participant statements revealed patterns of cognitive reconstruction centered around three conceptual cores. The first, transformational thinking (43%), was evident in epistemological shifts from fact memorization to systems thinking. Participants increasingly described biological phenomena as interconnected networks rather than isolated components. Creation-oriented perspectives emerged, with 67% of respondents describing a transition from knowledge consumers to knowledge producers. Specific transformations included modeling ecosystems instead of listing species (82 mentions), describing gene regulatory networks instead of memorizing enzymes (74 mentions), and employing computational methods alongside textbook learning (91 mentions).

The second theme, technological confidence (38% prevalence), reflected shifts in perceived capability. Anxiety related to programming markedly declined: average self-reported fear ratings dropped from 7.8/10 before the intervention to 2.3/10 afterward. Measures of technological self-efficacy showed substantial gains linked to specific tasks—confidence in Python coding increased by 412%, Arduino programming by 523%, and statistical analysis by 287%. Participants' perceptions of relevance changed dramatically: 89% recognized technology as a vital pedagogical tool, compared to only 31% at baseline.

The theme of motivation for innovation (31% prevalence) encompassed future-oriented aspirations. Several participants reported plans to establish bio hackspaces (n=19), and interest in graduate programs shifted notably toward computational biology, with 47% expressing interest compared to only 8% prior to the intervention. Entrepreneurial thinking also emerged, as 23% of students conceptualized biotechnology startup ideas. Indicators of innovation were quantified through creative outputs: participants generated an average of 4.7 new instructional ideas post-intervention, compared to 1.2 prior, and proposed an average of 6.3 suggestions for technological integration per participant.

Faculty observations (n=8) corroborated student-reported outcomes. Increased engagement was reflected in earlier arrival times—on average, students arrived 52 minutes before the start of class. Interdisciplinary connections were evidenced by cross-referencing assignments: biological concepts were identified in 73% of mathematics homework submissions. However, the shift in pedagogical paradigm introduced instructional challenges. Instructors required, on average, 34.7 hours to prepare for student-centered approaches, in contrast to 8.2 hours for preparing traditional lectures, highlighting the additional time demands associated with innovative instructional practices.

4. DISCUSSION

The motivational effects of STEM-based pedagogy observed in this study align with international findings. The 86.9% increase in self-efficacy corresponds with outcomes reported in Vietnam, where STEM-oriented subjects have been shown to enhance students' problem-solving and creative competencies [29]. The role of prior preparation appears to be context-dependent. International literature emphasizes that teacher readiness—encompassing knowledge, skills, and attitudes—is a prerequisite for effective STEM implementation [30]. However, the current study demonstrates the effectiveness of STEM-based instruction even among participants with no prior technological experience (initial Python proficiency: 0%). The effect size (d=1.89) exceeded those reported in comparable longitudinal studies. A 16-week intervention involving 148 pre-service STEM teachers revealed substantial competency gains through digitally supported incremental scaffolding [31]. A meta-analytic synthesis of STEM professional development programs documents aggregate effects on teacher self-efficacy, providing a benchmark for individual studies [32]. "Research Experiences for Teachers" programs produced an effect of 0.330 standard deviations at the student level in STEM career awareness [33]. The magnitude of the effect observed in the present study may reflect the intensive format of the intervention (20 weeks compared to the more typical 8–12 weeks). A Spanish study examining expectancy, value, and cost factors identified a moderating influence of perceived barriers on STEM integration outcomes [34]. A systematic synthesis of 510 publications across 27 reviews (2010–2024) indicates that effect size is contingent upon intervention design features, including duration, feedback cycles, and the integration of content and pedagogy [5].

The expansion of the TPACK framework for biological STEM education necessitates moving beyond traditional domain intersections. The present findings highlight the integration of sociocultural knowledge that extends beyond the core intersection of technology, pedagogy, and content [35]. Biology, as a disciplinary context, requires unique configurations of technological pedagogical CK. Tools such as Arduino biosensors, bioinformatics platforms, and VR-based molecular visualizations demand discipline-specific competencies that are inadequately addressed by generalized STEM-TPACK models [36].

These results support the adoption of the digital pedagogical and content knowledge (DPACK) framework, in which digital cultural transformations complement the existing components of TPACK. Biology educators must not only master subject content but also navigate the broader digitalization of society [35]. Collaborative discourse analysis reveals a dynamic process of mutual knowledge exchange between individual teachers' TPACK and the shared knowledge generated through collaboration. Project-based methodologies—adopted by 100% of participants—exemplify this collective construction of professional expertise [37].

The emergence of AI-TPACK further complicates the knowledge architecture. Various knowledge domains exhibit differing levels of explanatory power, with technology-related components exerting a particularly strong influence. Biological STEM competencies, as evidenced in this study, manifest through the integrated application of knowledge rather than the additive accumulation of discrete skills. Notably, 89% of participants achieved intermediate to expert-level proficiency in Python as a result of applying the language to authentic biological problems.

The absence of full randomization limits the ability to establish a causal relationship between the intervention and the observed changes. Self-selection bias may have resulted in the inclusion of more highly motivated participants in the EG; consequently, estimates of intervention effectiveness may be inflated. The homogeneity of the sample (three universities from a single region) constrains the generalizability of the findings to other Central Asian countries with differing educational traditions and infrastructures. Replication studies in Uzbekistan, Kyrgyzstan, and Tajikistan are required to confirm the cross-cultural applicability of the proposed model. The 12-week duration of the intervention may be insufficient to assess the durability of the competencies formed, and without a delayed post-test (6–12 months), long-term skill retention cannot be evaluated. The Hawthorne effect (the influence of observer presence) may have led to inflated engagement indicators. Self-efficacy self-assessments are also susceptible to social desirability bias; therefore, the interpretation of subjective ratings requires caution.

The contribution of transformative learning is reflected in the documented shifts in perspective among participants: 43% experienced a cognitive transformation from fact accumulation to systems thinking—an outcome aligned with the principles of transformative learning, wherein individuals reinterpret prior experiences to form new meaning structures [38]. The substantial increase in self-efficacy (86.9%) exemplifies the operationalization of Mezirow's framework. Participants reconstructed their beliefs about their own capabilities through critical reflection on their assumptions, values, and paradigms [39]. The magnitude of these changes is consistent with international findings. The observed rise in self-efficacy mirrors results from Vietnam, where STEM-oriented curricula have been shown to enhance student competencies in problem-solving and creativity.

5. CONCLUSION

Subject-matter knowledge increased by 42.2% (from 22.3 to 31.7) among participants in the EG, compared to a 14.9% gain (from 22.1 to 25.4) in the CG. This difference confirms the pedagogical effectiveness of the intervention ($p<0.001$, $d=1.89$). The most substantial improvement was observed in molecular biology, where the EG exhibited a 57.7% increase (from 7.8 to 12.3), in contrast to 18.2% (from 7.7 to 9.1) in the CG. The integration of bioinformatics contributed to a conceptual reorganization of knowledge in this domain. Technological competence emerged through a progressive learning trajectory. Python proficiency reached intermediate to advanced levels in 89% of the EG, starting from a baseline of zero. Similarly, 78% achieved advanced to expert-level competence in Arduino. DNA sequence analysis success rates (91.9% in the EG vs. 22.6% in the CG) quantitatively reflected the development of algorithmic thinking. Achievements in biosensor programming (85.5% vs. 0%) demonstrated the operationalization of hardware–software integration. Practical implementation was evident in economically efficient innovations. The BioSense school initiative reduced equipment costs by 91% ($45 vs. $500) while maintaining measurement accuracy ($pH\pm0.01$; $O_2\pm0.5\%$). The gene explorer VR platform achieved a 96% engagement rating, with an 82% 72-hour knowledge retention rate. The scientific contribution of this study lies in validated structures for STEM–biology integration, adapted to the educational context of Central Asia. Scalability pathways include: the modernization of secondary school curricula through the integration of computational biology modules; teacher professional development programs incorporating Arduino, Python, and VR technologies; and educational policy reforms that recognize the importance of interdisciplinary competencies. BioPredict AI applications facilitate citizen science initiatives, achieving 87% species identification accuracy, thereby democratizing biodiversity monitoring. Entrepreneurial trajectories also emerged: 23% of participants conceptualized biotechnology startups, and 47% reoriented their post-graduation goals toward computational biology.

Future research should focus on longitudinal tracking of competency retention over 3–5 years and examine career trajectories to document the sustainability of STEM integration. Rural schools will require adapted implementation protocols that consider infrastructural constraints, such as offline Python environments, battery-powered Arduino systems, and preloaded VR content. Priority should be given to long-term studies and multi-institutional trials across diverse infrastructural conditions. Economic impact assessments must include indicators such as reduced laboratory costs, increased student motivation, and improved employability. Data collection and systematization are essential for such evaluations. Several questions remain unresolved. It is unknown whether participants retain the competencies developed 2–3 years after program completion, and the transformation of these skills within authentic teaching practice has not yet been examined. The influence of school organizational culture on graduates' capacity to implement STEM methods also warrants investigation. Furthermore, the minimum level of technological infrastructure required to reproduce the observed outcomes in rural schools has not been established.

Additionally, research is needed on mechanisms for scalability—support structures and professional learning communities can enable systemic change beyond individual classrooms. Professional development programs are designed for a 12-week duration (3 hours per week) in a modular format: Python (4 weeks), Arduino (4 weeks), and VR/AR (4 weeks); the practice-to-theory ratio is 60:40. Resource provision: the minimum equipment set for a group of 30 participants amounts to USD 1,350 (Arduino kits at USD 45 each); software is open-access (Python, QGIS, open VR platforms); instructor training requires 35 hours. Adaptation to resource-constrained settings includes offline versions of Python modules, battery-powered Arduino systems, and preloaded VR content enabling operation without Internet connectivity. Institutional partnership is recommended through collaboration between universities and information technology (IT) companies (internships, mentorship) as well as ministries of education (integration into professional standards).

FUNDING INFORMATION

Authors state no funding involved.

AUTHOR CONTRIBUTIONS STATEMENT

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

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Symbat Ibadulla		✓		✓		✓				✓				
Kalampyr Zhumagulova	✓			✓	✓		✓			✓		✓		
Gulmira Zhussipova		✓		✓	✓				✓					✓
Makhabbat Amanbayeva	✓		✓	✓		✓			✓				✓	
Gani Issayev	✓	✓		✓	✓				✓		✓			
Ardak Bostanova	✓			✓	✓		✓	✓		✓				

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

INFORMED CONSENT

Informed consent was signed by participants.

ETHICAL APPROVAL

The research was conducted ethically in accordance with the World Medical Association Declaration of Helsinki. The study was approved at the meeting of the Ethics Committee of Abai Kazakh National Pedagogical University (Protocol no. 480FI dated from 18.08.2024).

DATA AVAILABILITY

The authors confirm that the data supporting the findings of this study are available within the article [and/or its supplementary materials].

REFERENCES

[1] J. S. Meuleners *et al.*, "Are Digital Tools More Often Implemented in High-Quality Lessons?—Profiles of Instructional Quality and the Use of Digital Tools in Biology and Mathematics Lessons," *International Journal of Science and Mathematics Education*, vol. 23, no. 5, pp. 1439–1465, Jun. 2025, doi: 10.1007/s10763-024-10510-1.

[2] Z. Zhan and S. Niu, "Subject integration and theme evolution of STEM education in K-12 and higher education research," *Humanities and Social Sciences Communications*, vol. 10, no. 1, p. 781, Nov. 2023, doi: 10.1057/s41599-023-02303-8.

[3] Z. Yesmakhanova, A. Abubakirova, and S. Nurzhanova, "Digital Formation of Competences for Future Biology Teachers in Blended Learning," (in Ukranian), *Journal of Educational Sciences*, vol. 79, no. 2, pp. 83–92, 2024, doi: 10.26577/JES2024790207.

[4] D. J. Shernoff, S. Sinha, D. M. Bressler, and L. Ginsburg, "Assessing teacher education and professional development needs for the implementation of integrated approaches to STEM education," *International Journal of STEM Education*, vol. 4, no. 1, p. 13, Dec. 2017, doi: 10.1186/s40594-017-0068-1.

[5] J. König *et al.*, "Effectiveness of interventions in teacher education: Synthesis of reviews (2010–2024)," *Zeitschrift für Erziehungswissenschaft*, vol. 28, no. 6, pp. 1345–1388, Dec. 2025, doi: 10.1007/s11618-025-01319-x.

[6] H.-E. Chu, S. N. Martin, and J. Park, "A Theoretical Framework for Developing an Intercultural STEAM Program for Australian and Korean Students to Enhance Science Teaching and Learning," *International Journal of Science and Mathematics Education*, vol. 17, no. 7, pp. 1251–1266, Oct. 2019, doi: 10.1007/s10763-018-9922-y.

[7] M. Jones *et al.*, "Learning contexts and visions for STEM in schools," *International Journal of Science Education*, vol. 47, no. 3, pp. 337–357, Feb. 2025, doi: 10.1080/09500693.2024.2323032.

[8] S. Ibadulla, K. Zhumagulova, and A. Maimatayeva, "Creating a STEAM project with students as an indicator of the effectiveness of training future biologists," *Scientific Herald of Uzhhorod University Series Physics*, no. 56, pp. 1767–1776, Mar. 2024, doi: 10.54919/physics/56.2024.176dy7.

[9] N. Zhang and Y. Liu, "Design and implementation of virtual laboratories for higher education sustainability: a case study of Nankai University," *Frontiers in Education*, vol. 8, Jan. 2023, doi: 10.3389/feduc.2023.1322263.

[10] C. Babaian and S. Kumar, "Storyboarding for Biology," *The American Biology Teacher*, vol. 84, no. 6, pp. 328–335, Aug. 2022, doi: 10.1525/abt.2022.84.6.328.

[11] M. C. de la Hoz, A. Solé-Llussà, J. Haro, N. Gericke, and C. Valls, "Student Primary Teachers' Knowledge and Attitudes Towards Biotechnology—Are They Prepared to Teach Biotechnological Literacy?" *Journal of Science Education and Technology*, vol. 31, no. 2, pp. 203–216, Apr. 2022, doi: 10.1007/s10956-021-09942-z.

[12] N. H. Diep, V. T. T. Hoai, P. N. Son, P. T. Nga, H. T. P. Thuy, and N. M. Duc, "Developing competencies of natural science teachers for designing and organizing STEM education activities in Vietnam," *International Journal of Education and Practice*, vol. 11, no. 3, pp. 500–514, Aug. 2023, doi: 10.18488/61.v11i3.3430.

[13] B. M. Reynante, M. E. Selbach-Allen, and D. R. Pimentel, "Exploring the Promises and Perils of Integrated STEM Through Disciplinary Practices and Epistemologies," *Science & Education*, vol. 29, no. 4, pp. 785–803, Aug. 2020, doi: 10.1007/s11191-020-00121-x.

[14] J. D. Ermakova and T. M. Nosova, "Professional Teacher Training in the Context of Digitalization of Education," *Izvestiya of the Samara Science Centre of the Russian Academy of Sciences. Social, Humanitarian, Medicobiological Sciences*, vol. 25, no. 91, pp. 34–44, 2023, doi: 10.37313/2413-9645-2023-25-91-34-44.

[15] T. I. Anisimova, F. M. Sabirova, and O. V. Shatunova, "Formation of design and research competencies in future teachers in the framework of STEAM education," *International Journal of Emerging Technologies in Learning*, vol. 15, no. 2, pp. 204–217, Jan. 2020, doi: 10.3991/ijet.v15i02.11537.

[16] B. Zharmenova, R. Kurmanbayev, G. Tulindinova, R. Zhandavletova, and B. Zhussipbek, "Environmental education as part of the training of future biologists at the university," *Scientific Herald of Uzhhorod University Series Physics*, no. 55, pp. 2549–2558, Feb. 2024, doi: 10.54919/physics/55.2024.254so9.

[17] G. I. Issayev, D. Z. Yussupova, and A. I. Issayev, "Forming Students' Research Skills by Implementing Stem Technologies in the Subject of Biology," (in Russian), *Bulletin of The National Academy of Sciences of The Republic of Kazakhstan*, vol. 406, no. 6, pp. 153–168, Dec. 2023, doi: 10.32014/2023.2518-1467.624.

[18] J. A. Luft, D. Hanuscin, L. Hobbs, and G. Törner, "Out-of-Field Teaching in Science: An Overlooked Problem," *Journal of Science Teacher Education*, vol. 31, no. 7, pp. 719–724, Oct. 2020, doi: 10.1080/1046560X.2020.1814052.

[19] K. Watts and W. Richardson, "Inclusive Pedagogy Strategies to Introduce High Schoolers to Systems Biology," *Biomedical Engineering Education*, vol. 4, no. 1, pp. 87–96, Jan. 2024, doi: 10.1007/s43683-023-00127-1.

[20] B. Huang, M. Siu-Yung Jong, Y. F. Tu, G. J. Hwang, C. S. Chai, and M. Yi-Chao Jiang, "Trends and exemplary practices of STEM teacher professional development programs in K-12 contexts: A systematic review of empirical studies," *Computers and Education*, vol. 189, p. 104577, Nov. 2022, doi: 10.1016/j.compedu.2022.104577.

[21] K. C. Margot and T. Kettler, "Teachers' perception of STEM integration and education: a systematic literature review," *International Journal of STEM Education*, vol. 6, no. 1, p. 2, Dec. 2019, doi: 10.1186/s40594-018-0151-2.

[22] L. C. Valle, R. R. Gonzales, R. M. L. Almacen, G. Batucan, and G. G. Gonzales, "Modeling the relationship of the TPACK framework with cyber wellness, school climate, and digital nativity of basic education teachers," *Frontiers in Education*, vol. 9, Jul. 2024, doi: 10.3389/feduc.2024.1397888.

[23] A. Kintonova, A. Sabitov, I. Povkhan, D. Khaimulina, and G. Gabdreshov, "Organization of Online Learning Using the Intelligent Metasystem of Open Semantic Technology for Intelligent Systems," *Eastern-European Journal of Enterprise Technologies*, vol. 1, no. 1, pp. 29–40, Feb. 2023, doi: 10.15587/1729-4061.2023.272952.

[24] T. R. Kelley, J. G. Knowles, J. D. Holland, and J. Han, "Increasing high school teachers self-efficacy for integrated STEM instruction through a collaborative community of practice," *International Journal of STEM Education*, vol. 7, no. 1, p. 14, Dec. 2020, doi: 10.1186/s40594-020-00211-w.

[25] L. S. Bose and S. Humphreys, "The 5I's of Virtual Technologies in Laboratory Teaching for Faculties of Higher Education in Kerala," *Journal of Science Education and Technology*, vol. 31, no. 6, pp. 795–809, Dec. 2022, doi: 10.1007/s10956-022-09995-8.

[26] F. Ruparanganda, "Challenges faced by Biology Secondary teachers when using instructional methods that promote Science Technology, Engineering and Mathematic (STEM) Education in Zimbabwe," *Texila International Journal of Academic Research*, vol. 6, no. 2, pp. 106–111, Oct. 2019, doi: 10.21522/tijar.2014.06.02.art011.

[27] K.-Y. Lin, H.-S. Hsiao, P. J. Williams, and Y.-H. Chen, "Effects of 6E-oriented STEM practical activities in cultivating middle school students' attitudes toward technology and technological inquiry ability," *Research in Science & Technological Education*, vol. 38, no. 1, pp. 1–18, Jan. 2020, doi: 10.1080/02635143.2018.1561432.

[28] A. Struyf, H. De Loof, J. Boeve-de Pauw, and P. Van Petegem, "Students' engagement in different STEM learning environments: integrated STEM education as promising practice?" *International Journal of Science Education*, vol. 41, no. 10, pp. 1387–1407, Jul. 2019, doi: 10.1080/09500693.2019.1607983.

[29] H. T. Nguyen, L. T. N. Nguyen, Q. H. Nguyen, T. Q. Tu, and M. H. Chu, "Developing principles and steps for integrating bioinformatics into teaching for pedagogical university students: A case study in Vietnam," *International Journal of Education and Practice*, vol. 13, no. 2, pp. 520–535, Jan. 2025, doi: 10.18488/61.v13i2.4070.

[30] S. Talib, B. S. Alias, and M. E. Mohd Matore, "Principal Competency, Teacher Readiness, and Teacher Commitment in STEM Education Implementation: A Qualitative Study," *e-Bangi Journal of Social Science and Humanities*, vol. 20, no. 4, Nov. 2024, doi: 10.17576/ebangi.2024.2104.30.

[31] M. Offermann *et al.*, "The development of pre-service biology teachers' intention to use digital incremental scaffolds: insights from guided online training," *Frontiers in Psychology*, vol. 16, Oct. 2025, doi: 10.3389/fpsyg.2025.1656795.

[32] J. Liu, K. Wang, and Z. Pan, "The Effectiveness of Professional Development in the Self-Efficacy of In-Service Teachers in STEM Education: A Meta-Analysis," *Behavioral Sciences*, vol. 15, no. 10, p. 1364, Oct. 2025, doi: 10.3390/bs15101364.

[33] J. Keller *et al.*, "Impact of Teachers with Research Experiences: Student Gains in STEM Career Awareness, Perception of Value of STEM Learning, and Persistence in STEM Course Tasks," *Science Education*, vol. 109, no. 3, pp. 769–795, May 2025, doi: 10.1002/sce.21926.

[34] R. B. Toma, A. García-Carmona, and J. Quílez, "Are Integrated STEM Educational Reforms at Risk? Teachers' Motivations and Perceived Barriers to Integration," *Journal of Research in Science Teaching*, vol. 62, no. 10, pp. 2238–2254, Dec. 2025, doi: 10.1002/tea.70026.

[35] C. Thyssen, J. Huwer, T. Irion, and S. Schaal, “From TPACK to DPACK: The ‘Digitality-Related Pedagogical and Content Knowledge’-Model in STEM-Education,” *Education Sciences*, vol. 13, no. 8, p. 769, Jul. 2023, doi: 10.3390/educsci13080769.

[36] C. Fei and A. W. C. Tse, “Examining the Technological Pedagogical Content Knowledge (TPACK) of Biology Educators: A Case Study on Pre-service and In-service Teachers in Preparation for Applying STEM Education,” in *Emerging Technologies for Education: 8th International Symposium, SETE 2023*, Sydney, Australia, November 26–28, 2023, Revised Selected Papers, Part I, vol. 14606 LNCS, Z. Kubincová, T. Hao, N. Capuano, M. Temperini, S. Ge, Y. Mu, P. Fantozzi, and J. Yang, Eds., Berlin, Heidelberg: Springer-Verlag, 2024, pp. 94–110, doi: 10.1007/978-981-97-4243-1_8.

[37] Y. F. Yeh, K. K. H. Chan, and Y. S. Hsu, “Toward a framework that connects individual TPACK and collective TPACK: A systematic review of TPACK studies investigating teacher collaborative discourse in the learning by design process,” *Computers and Education*, vol. 171, p. 104238, Oct. 2021, doi: 10.1016/j.compedu.2021.104238.

[38] A. L. McClain, “New Developments in Transformative Learning,” *New Directions for Adult and Continuing Education*, vol. 2024, no. 184, pp. 20–29, Dec. 2024, doi: 10.1002/ace.20540.

[39] L. A. Wolff *et al.*, “Editorial: Transformative learning, teaching, and action in the most challenging times,” *Frontiers in Education*, vol. 7, Dec. 2022, doi: 10.3389/feduc.2022.1041914.

BIOGRAPHIES OF AUTHORS

Symbat Ibadulla holds a Master of Educational Sciences and doctoral student. She works at Department of Biology, Abai Kazakh National Pedagogical University. Symbat’s research interests include: biology education; STEM education, project-based learning (PBL), problem-based learning; professionalism; technological progress, and competency-based approach. She can be contacted at email: s.ibadulla@abaiuniversity.edu.kz.

Kalampyr Zhumagulova is candidate of Pedagogical Sciences. She is a professor of Department of Biology, Abai Kazakh National Pedagogical University. Kalampyr’s research interests include: teaching methods, formative assessment, critical thinking, practice-oriented learning, and inquiry-based learning. She can be contacted at email: k.zhumagulova@abaiuniversity.edu.kz, kalazhumagulova@alibagl.com.

Gulmira Zhussipova is a candidate of Biological Sciences, senior lecturer in Ozbekali Zhanibekov South Kazakhstan Pedagogical University, Faculty of Physical Education and Sport, Department of Initial Military Training and Physical Education. Gulmira’s research interests include: scientific inquiry, data literacy, computational thinking, modeling, and simulation. She can be contacted at email: gulmir22@mail.ru.

Makhabbat Amanbayeva is Ph.D. She is an associate professor of Department of Biology, Abai Kazakh National Pedagogical University. Makhabbat’s research interests include: biology education; digital competence; digitalization; information and communication technologies; professionalism; and technological progress. She can be contacted at email: m.amanbayeva@outlook.com.

Gani Issayev is candidate of Tehnical Saiences, associate professor. He works as senior lecturer at Department of Biology, Khoja Akhmet Yassawi International Kazakh-Turkish University, Turkestan, Republic of Kazakhstan. Gani's research interests include: biology education; digital competence; digitalization; information and communication technologies; professionalism; and technological progress. He can be contacted at email: ganiissayev77@outlook.com.

Ardak Bostanova is candidate of Biological Sciences, senior lecturer. She works as senior lecturer at Department of Biology, Khoja Akhmet Yassawi International Kazakh-Turkish University, Turkestan, Republic of Kazakhstan. Ardak research interests include biology education; digital competence; digitalization; information and communication technologies; professionalism; and technological progress. She can be contacted at email: ardak.bostanova@ayu.edu.kz.