Enhancing Master's-Level STEM Education through AI-Driven IoT Projects: A Kazakhstan Experiment

Meruert Serik[1], Kymbat Tleuzhanova[1], and Symbat Nurgaliyeva[2,*]

[1]Department of Computer Science, L.N. Gumilyov Eurasian National University, Astana, Kazakhstan
[2]Department Computer Engeneering, Astana IT University, Astana, Kazakhstan
Email: serik_meruerts@mail.ru (M.S.); bazylkhan_kymbat@mail.ru (K.T.); symbat.nurgaliyeva@astanait.edu.kz (S.N.)
*Corresponding author

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***Abstract*—In developing contexts such as Kazakhstan, Science, Technology, Engineering and Math (STEM) education at the master's level continues to prioritize theoretical instruction, while offering insufficient exposure to the practical integration of emerging technologies. This study was conducted in response to the increasing demand for experiential, hands-on education in Artificial Intelligence (AI) and the Internet of Things (IoT), which are essential for preparing students for the digital economy. The research examines the integration of emerging technologies into master-level STEM education through an AI- and IoT-based system that merges Machine Learning (ML) and IoT, supported by AI and Deep Learning (DL), and delivered via Project-Based Learning (PBL). A mixed-method design was employed, including pre-test and post-test assessments and project-based evaluations to measure student motivation, content knowledge, and practical skills. The study involved 167 master's students from two universities, divided into an experimental group utilizing AI-IoT projects and a control group following a traditional lecture-based curriculum. Statistical analysis using Pearson's Chi-square test revealed significant improvements in motivation ($\chi^2 = 14.95$), conceptual understanding ($\chi^2 = 10.50$), and practical competencies ($\chi^2 = 12.92$) in the experimental group ($p < 0.05$). These findings confirm the effectiveness of AI-supported PBL in enhancing STEM education outcomes.**

***Keywords*—Artificial Intelligence (AI) in education, machine learning, internet of things, Science, Technology, Engineering and Math (STEM) education, project-based learning**

I. Introduction

Emerging technologies such as Artificial Intelligence (AI), Machine Learning (ML)—including Deep Learning (DL) as an advanced subset-process automation, biometric recognition, and natural language processing are significantly reshaping various sectors, including education. As AI continues to evolve, its integration into educational settings has been widely studied, demonstrating its potential to enhance student engagement, learning outcomes, and technical proficiency [1, 2].

Despite this growing body of research, limited attention has been given to adapting these technologies within regional educational frameworks, particularly in countries like Kazakhstan, where Science, Technology, Engineering and Math (STEM) programs at the master's level often lack systematic, project-based training in AI and IoT applications. While some initiatives exist to modernize STEM education in Kazakhstan, full-scale integration remains embryonic, with adoption predominantly limited to undergraduate pilot projects.

Recent studies also reveal that practical implementation of AI and IoT remains largely confined to short-term, undergraduate-focused initiatives [3–5]. Moreover, Kakoulli *et al.* [6] demonstrate that hands-on experience with AI and IoT technologies is essential for developing advanced technical skills required in the modern digital economy. Zawacki-Richter *et al.* [7] and Chen *et al.* [8] highlight that AI and IoT integration in higher education remains underdeveloped in developing regions due to legacy academic models and resource limitations. Guo and Li [9] further emphasize the transformative potential of IoT-driven analytics in education while noting the slow pace of institutional adoption.

In contrast to previous studies, the present research integrates AI and IoT technologies within a structured, semester-long Project-Based Learning (PBL) framework tailored specifically for master's-level STEM education. It employs a mixed-method approach combining quantitative (pre-test and post-test assessments) and qualitative (project evaluations) techniques to assess the effectiveness of this integration. Prior studies have often examined these technologies in isolation, focusing on undergraduates and short-term implementations [10, 11]. Moreover, the current study simultaneously evaluates student motivation, conceptual understanding, and practical competencies—areas frequently treated separately in earlier research. Additionally, the study is situated within Kazakhstan's higher education system, offering locally relevant pedagogical solutions that respond to institutional challenges.

Although AI and IoT adoption in global education is advancing, their implementation in postgraduate STEM curricula-particularly in developing countries-remains limited and primarily theoretical. Studies by Joseph and Uzondu [12] and Gkrimpizi *et al.* [13] indicate that, despite curricular reforms, many universities still lack the infrastructure, faculty readiness, and pedagogical models needed to effectively implement AI and IoT-based project learning. Consequently, students are often disengaged and underprepared to apply their knowledge in real-world contexts, limiting both motivation and skill development.

The investigation situates ML within the broader AI landscape, illustrating how DL techniques can further optimize the analysis of large-scale IoT-generated data. By presenting this extended theoretical foundation, the study emphasizes the role of AI-driven approaches in bridging the gap between conceptual learning and applied problem-solving in advanced STEM education.

To address these challenges, the research explores the practical integration of AI-driven ML and IoT technologies in STEM education, specifically within Kazakhstan's academic

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context. Previous studies have demonstrated that incorporating AI, IoT, and robotics into education can significantly enhance students' technical competencies and career readiness for technology-driven fields [14, 15]. However, the localized, sustained application of these technologies in master's-level curricula remains underexplored. While many researchers have assessed AI and IoT tools in undergraduate education, few have evaluated their combined impact in a postgraduate environment, reinforcing the novelty of this work.

In January 2019, L.N. Gumilyov Eurasian National University (ENU) became a member of the European ERASMUS+ project, "Integrated Approach to the Training of STEM Teachers." This international collaboration seeks to enhance the quality of STEM teacher training in line with the Bologna Process and the evolving demands of the knowledge economy [16]. Building on this initiative, ENU has implemented innovative learning approaches that prioritize active, hands-on engagement and the development of essential 21st-century skills.

The primary objective of this study is to evaluate the effectiveness of integrating AI-driven ML and IoT technologies into STEM education through project-based learning, with the goal of narrowing the gap between theoretical coursework and practical application in Kazakhstan's master's programs. To achieve this, three IoT-based projects—focused on face recognition, gesture recognition, and speech recognition - were implemented to simulate real-world challenges in domains such as security, automation, and smart environments. These projects enabled students to apply ML algorithms in realistic, problem-solving contexts.

Based on the literature-informed problem statement and the study's pedagogical context, the following hypotheses were formulated to guide the research:

Null Hypothesis (H_0): The integration of IoT-based projects into master's-level STEM education does not result in statistically significant differences in student motivation, conceptual understanding, or practical skills compared to traditional lecture-based instruction.

Alternative Hypothesis (H_1): The integration of IoT-based projects into master's-level STEM education results in statistically significant improvements in student motivation, conceptual understanding, and practical skills.

This study makes several significant contributions. First, it provides empirical evidence on the effectiveness of integrating AI-driven ML and IoT technologies through PBL at the master's level—an area that remains largely unexplored in Kazakhstan. Second, by bridging the gap between theoretical instruction and practical application, our work offers a novel framework that can inform curriculum design and pedagogical strategies in STEM education. Finally, the findings have broad implications for policymakers and educators, emphasizing the urgent need to modernize educational practices to prepare students for the digital economy.

II. Literature Review

The integration of AI, ML and IoT in STEM education has demonstrated significant potential in personalizing learning, automating assessments, and enhancing student engagement. However, prior studies have largely focused on undergraduate applications, while their structured incorporation into master's STEM curricula remains limited. This overview of the literature looks at important research findings, points out gaps, and emphasizes the necessity of a methodical approach to incorporating AI and IoT in graduate-level PBL.

A. AI and IoT in STEM Education

AI and IoT technologies have transformed education by enabling real-time data analysis, facilitating adaptive learning, and supporting automated feedback systems. Das *et al.* [17] highlight that AI-powered platforms adjust learning paths dynamically, providing students with personalized content recommendations based on their progress. Similarly, Pradeep [18] demonstrate that IoT-based educational tools offer real-time monitoring and assessment, ensuring that instructors can intervene when students struggle. Espinosa *et al.* [19] further emphasize that predictive analytics powered by AI enhances decision-making in STEM education, allowing institutions to refine their instructional strategies. This study underscores AI and IoT's transformative impact on data-driven learning, yet existing research remains largely confined to undergraduate education. By introducing a structured AI-IoT framework tailored for STEM master's programs, this work bridges a critical gap and establishes a scalable model for advanced education.

B. PBL and Emerging Technologies

PBL has gained recognition for enhancing problem-solving skills, fostering critical thinking, and promoting interdisciplinary collaboration. Johnson and Delawsky [20] highlight that AI-enhanced PBL allows students to apply theoretical knowledge to real-world challenges, leading to deeper engagement and knowledge retention. Ruiz *et al.* [21] emphasize that AI-supported PBL models incorporate automated feedback mechanisms and interactive simulations, ensuring continuous skill development. Furthermore, Bagheri *et al.* [22] found that integrating AI and IoT into PBL encourages self-directed learning and industry-aligned skill acquisition, making students more adaptable to evolving technological demands. This study advances AI-driven PBL from undergraduate-focused research to master's-level STEM education, promoting experiential learning and addressing critical gaps in curriculum development through empirical analysis.

C. The Role of AI and IoT in Enhancing Real-World Problem Solving

AI and IoT technologies are increasingly used to simulate real-world scenarios, helping students develop analytical, technical, and decision-making skills. Omarov *et al.* [23] discuss how AI-powered learning platforms offer dynamic problem-solving simulations, preparing students for real-time, industry-based challenges. Al-Zoubi *et al.* [24] emphasize that IoT-based smart environments enhance experiential learning, allowing students to analyze real-time sensor data and apply AI-driven analytical models. Additionally, Aldowah *et al.* [25] highlight how AI-powered tools enable learners to work with predictive models, automation, and robotics, fostering a deeper understanding of applied AI concepts. This study bridges the gap between industry applications and academic frameworks by introducing a structured AI-IoT-driven problem-solving model, ensuring its relevance and practical implementation in STEM master's education.

This literature review highlights the critical role of AI, IoT, and PBL in transforming STEM education. Previous studies emphasize the effectiveness of AI-driven adaptive learning and IoT-enabled hands-on experiences, particularly in enhancing problem-solving skills and technical proficiency. Constructivist learning theory and experiential learning principles provide a strong foundation for designing technology-integrated graduate-level curricula. This study builds upon these insights by proposing a structured AI-IoT-driven PBL framework tailored for STEM master's programs, addressing existing research gaps. Future research should further investigate scalability, long-term impact, and interdisciplinary applications to enhance AI-driven learning environments in higher education.

III. Materials and Methods

This study employed an experimental research design to examine the integration of ML and IoT-based projects into STEM education. The research methodology was divided into three distinct phases (Fig. 1): Preparation, Implementation, and Evaluation.

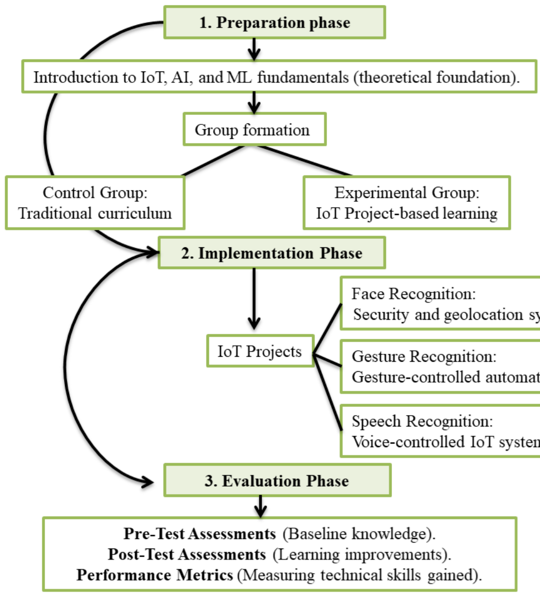


Fig. 1. Experiment design.

A. Preparation Phase

The preparation phase focused on establishing a baseline understanding of AI, ML, and IoT concepts among students and forming the experimental and control groups.

Table 1. Distribution of participants by university and group

University name and specialty	Experimental group	Control group
L.N. Gumilyov Eurasian National University, 7M01525-STEM education	88 students (37 male, 51 female)	
S. Amanzholov East Kazakhstan University, 7M01513-STEM education		79 students (29 male, 50 female)
Total	167 students (66 male, 101 female)	

Participants, the educational experiment was conducted during the first semester of the 2024–2025 academic year at L.N. Gumilyov Eurasian National University and S. Amanzholov East Kazakhstan University, both located in Kazakhstan. The participants were master's students enrolled in the educational program STEM education, specifically within the discipline of programming. A total of 167 students participated in the study, divided into two groups: 88 students in the control group and 79 students in the experimental group. The demographic distribution of participants, including age and gender, is summarized in Table 1.

Group Formation and Ethical Considerations, students were divided into teams of 4–6 members based on their academic background and skill sets. Age ranged from 22 to 26 years, with varying levels of programming experience. A pre-study survey confirmed that approximately 70% of participants had foundational knowledge of IoT and ML concepts**.**

Ethical Considerations, participation was voluntary, and informed consent was obtained from all students. The control group followed a traditional curriculum, ensuring no disadvantage for students who did not participate in the experimental work. The research adhered to ethical guidelines, ensuring transparency and fairness.

Pre-Test Assessment, as part of the Experimental Design**,** the 15-week study was structured into three distinct phases**.** During the preparation phase**,** a pre-test was administered to both the control and experimental groups to establish a baseline for measuring the impact of the intervention. This pre-test consisted of 15 structured questions, each targeting one of the following key learning components: Motivation (5 questions), Content Knowledge (5 questions), and Practical Skills (5 questions)**.** These categories were carefully designed to assess students' initial engagement levels, theoretical understanding of AI and IoT concepts, and their ability to apply technical skills in problem-solving contexts. The pre-test results provided a quantitative foundation for evaluating the effectiveness of the IoT- and ML-based PBL approach introduced in the subsequent phase of the study.

To ensure the reliability and validity of the pre-test and post-test instruments, a Cronbach's Alpha test was conducted to measure the internal consistency of the assessment items [26]. The Cronbach's Alpha coefficient for the pre-test was 0.83, and for the post-test, it was 0.86. A Cronbach's Alpha above 0.7 is considered acceptable for research instruments, demonstrating that the assessment items were reliable. A content validity analysis was performed by three independent experts in STEM education, AI, and IoT, who reviewed the test items to ensure alignment with learning objectives and construct validity.

To enhance transparency and accessibility, the complete set of pre-test and post-test questions is presented in Tables 2–4. The items are organized into three core learning components: motivation, content knowledge, and practical skills. Each component includes five targeted questions, designed to assess student engagement, conceptual understanding, and technical proficiency in the context of AI- and IoT-enhanced Project-based Learning (PBL).

Table 2. Motivation assessment items (pre-test/post-test)

Motivation component	
Question Type	**Example Question**
Likert Scale (1–5)	I feel confident in applying AI and IoT concepts to real-world problems.
Likert Scale (1–5)	Learning AI and IoT through project-based activities increases my interest in STEM subjects.
Likert Scale (1–5)	I believe IoT and ML skills will be valuable for my future career in STEM fields.
Likert Scale (1–5)	I am comfortable working in a team to develop AI-IoT-based solutions.
Likert Scale (1–5)	I prefer hands-on learning approaches rather than theoretical coursework.

Table 3. Content knowledge items (pre-test/post-test)

Content Knowledge component	
Multiple Choice	Which IoT communication protocol is most suitable for long-range, low-power applications?
Multiple Choice	Which algorithm is commonly used for facial recognition tasks?
Multiple Choice	What is the role of an Arduino in an IoT-based system?
Short Answer	Explain how AI enhances IoT applications in smart cities.
Short Answer	Describe one real-world example of IoT and ML integration in industrial automation.

Table 4. Practical skills items (pre-test/post-test)

Practical Skills component	
Hands-on Coding	Modify the given Python script to enable real-time facial recognition using OpenCV (Open Computer Vision) library.
Hands-on Coding	Write a program that sends sensor data from an IoT device to the cloud using MQTT (Message Queuing Telemetry Transport) protocol.
Hands-on Coding	Develop a simple voice recognition system using Python's SpeechRecognition library.
Project-Based Task	Design an IoT system that uses ML to detect hand gestures and control smart home devices.
Project-Based Task	Build a security system that unlocks a door when a known face is detected using ESP32-CAM.

To comprehensively evaluate student learning outcomes, the pre-test and post-test assessments were designed to collect both quantitative and qualitative data, covering three core learning components: motivation, content knowledge, and practical skills.

Motivation Assessment, motivation levels were evaluated using a 5-point Likert scale, allowing students to self-assess their confidence, interest, and engagement in AI and IoT-based learning. These survey-based responses provided quantitative data on students' perceived relevance of AI-IoT education to their academic development and future careers. Additionally, open-ended responses were collected to capture students' qualitative reflections on their learning preferences and attitudes toward hands-on, project-based education.

Content Knowledge Assessment, the assessment of theoretical knowledge utilized multiple-choice and short-answer questions to test students' understanding of AI, ML, and IoT concepts. Topics covered included IoT communication protocols, AI-driven facial recognition algorithms, and the role of microcontrollers in IoT systems. The multiple-choice format provided objective, quantitative evaluation, while the short-answer questions allowed for a deeper analysis of students' conceptual grasp, contributing to qualitative insights into their reasoning and problem-solving approaches.

Practical Skills Assessment, practical competency was measured using hands-on coding challenges and project-based tasks, reflecting students' ability to apply AI and IoT methodologies in real-world scenarios. Participants were required to:

- Modify Python scripts for real-time facial recognition using OpenCV.
- Implement MQTT-based sensor data transmission in IoT systems.
- Develop gesture-controlled automation for smart devices.
- Build a voice recognition system utilizing ML algorithms.

These assessments generated both quantitative performance scores (e.g., success rate in coding implementations) and qualitative feedback based on students' project reflections and debugging approaches. By integrating quantitative metrics (Likert-scale ratings, multiple-choice scores, coding task completion rates) with qualitative insights (open-ended responses, problem-solving reflections), the study ensured a comprehensive evaluation of student learning progression [27]. The combination of theoretical and applied assessments allowed for a robust measurement of the effectiveness of AI-IoT PBL in STEM education.

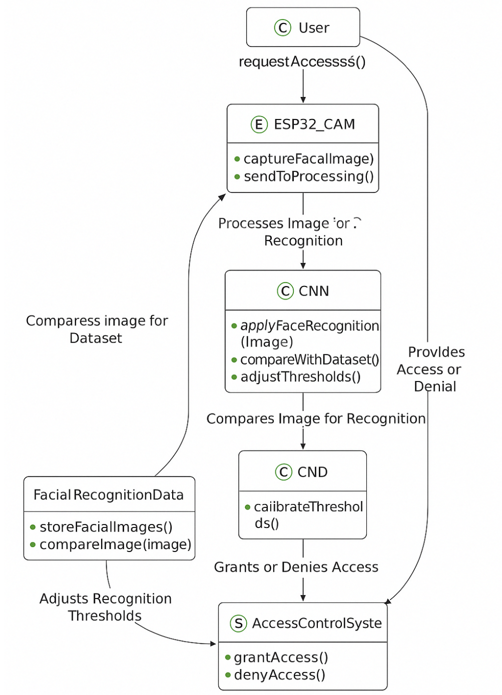
By structuring the assessment into these three categories, the study effectively measured students' baseline knowledge and skill levels, as well as their progress after participating in the IoT and ML based PBL approach. The inclusion of both theoretical and practical assessments ensured a comprehensive evaluation of student learning outcomes, directly addressing the objectives of the study.

B. Implementation Phase

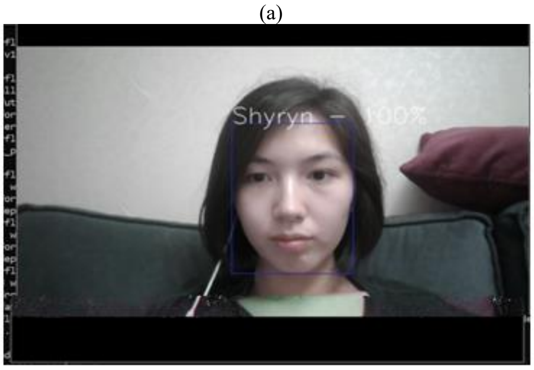
During the implementation phase**,** the experimental group engaged in a PBL approach that incorporated IoT-based solutions, while the control group followed a conventional curriculum centered on theoretical instruction and individual assignments. The PBL approach aimed to provide students with hands-on experience in applying ML and IoT technologies through three distinct projects: Face Recognition, Gesture Recognition, and Speech Recognition**.** These projects were selected based on their relevance to modern AI applications and their potential to enhance problem-solving skills in STEM education.

IoT Face recognition project based on ML, the Face recognition project involved using the ESP32-CAM face recognition module. The ESP32-CAM is a compact, energy-efficient camera module commonly used in IoT applications, including video surveillance, facial detection, and wireless image uploading [28]. Dokic demonstrated that the ESP32-CAM can support ML algorithms, such as binary logistic regression, for processing images, highlighting its capability to perform basic ML tasks [29].

The goal was for students to build a security system capable of identifying individuals based on their facial features and granting access to specific areas. ML algorithms, including Convolutional Neural Networks (CNN), were used to train the system to accurately detect and recognize faces from a dataset. The students were tasked with programming the system and calibrating the recognition thresholds to improve its performance. Fig. 2 presents the Unified Modeling Language (UML) Class Diagram illustrating the process where the system captures an individual's face, compares it with the most recent image of a suspect, and transmits the suspect's geolocation to a designated website.



(a)



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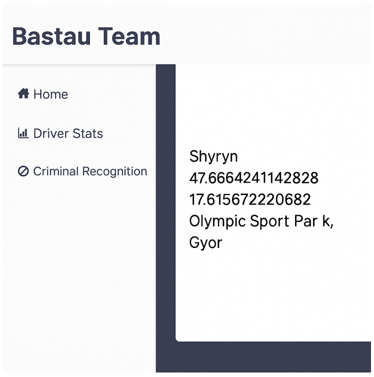
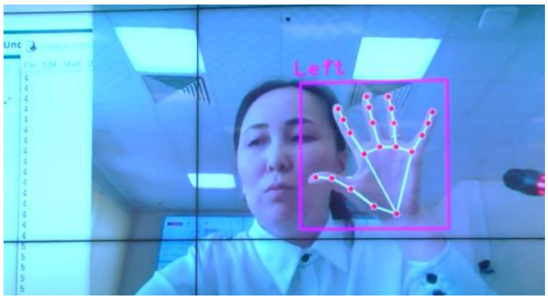


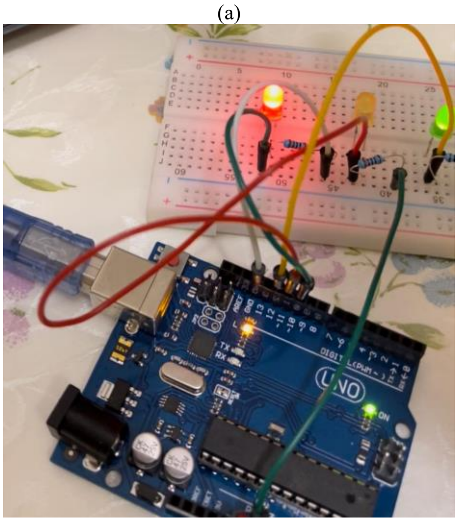
(c)

Fig. 2. General structure and implementation phases of the IoT-based face recognition system: (a) system architecture (UML diagram); (b) system testing during criminal identification phase; (c) data retrieval via web interface.

IoT Gesture recognition project based on ML: the Hand Recognition project utilizes the HandDetector module from the CVzone library to identify hand gestures, specifically the number of extended fingers, and transmit corresponding commands to an Arduino microcontroller. This enables the control of external devices, such as turning Light Emitting Diodes (LED) connected to the Arduino on or off. The primary objective of this project is to demonstrate the feasibility of controlling remote devices through the recognition of hand gestures, highlighting the potential for gesture-based human-computer interaction in various applications (Fig. 3).



(a)



(b)

Fig. 3. Smart fingerprint-based lighting control system: (a) testing the finger recognition process; (b) Arduino-based light control.

IoT Speech recognition project based on ML: the Speech Recognition project aimed to develop an IoT system that recognizes and responds to voice commands using the EasyVR3 Plus speech recognition module, specifically designed for Arduino boards. This module enables voice control for smart devices like lights and music players, as well as other applications such as managing household appliances and controlling robots [30, 31]. By incorporating ML algorithms, the system improves its recognition accuracy over time through continuous training on voice data. Students used Python programming and cloud-based AI tools to implement the system, which was then tested in real-world environments to evaluate its functionality and performance. Fig. 4 presents the UML Class Diagram illustrating the architecture of the IoT Speech Recognition project, which leverages ML techniques for voice command recognition and system efficiency.

This diagram outlines the key components and interactions within the system, illustrating the integration of voice recognition and IoT device control.

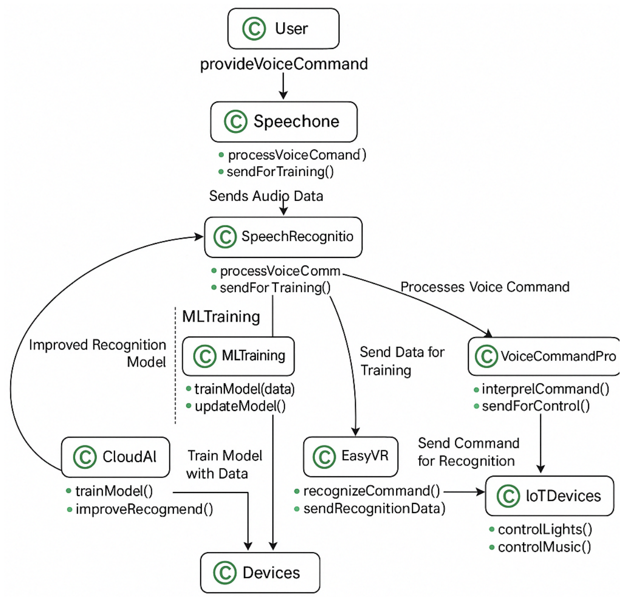


Fig. 4. UML diagram for IoT-based voice command recognition system.

C. *Evaluation Phase*

The evaluation phase was designed to assess the effectiveness of integrating AI and IoT-based PBL into STEM education. This phase consisted of a post-test assessment and statistical analysis, which aimed to quantify improvements in student learning outcomes compared to traditional theoretical instruction. The evaluation focused on three key learning components: motivation, content knowledge, and practical skills.

Post-Test Assessment, to measure students' progress, a post-test was administered following the completion of the IoT-based projects. The same 15-question test structure used in the pre-test was applied to ensure consistency and reliability in measurement. The post-test aimed to assess improvements in:

- Motivation—Changes in students' engagement and enthusiasm for learning AI and IoT concepts, which have been shown to be key indicators of effective STEM learning [2].
- Content Knowledge—Growth in students' theoretical understanding of AI and IoT principles, a factor emphasized by Kim *et al.* [6] in their study on AI-enhanced STEM education.
- Practical Skills—Students' ability to apply AI and IoT methodologies in real-world problem-solving scenarios, consistent with the findings of Zawacki-Richter *et al.* [7] on the role of hands-on learning in technology education.

By comparing pre-test and post-test results, the study provided a quantitative foundation for assessing the impact of the experimental intervention. The experimental group's performance was compared with that of the control group, which followed a traditional curriculum without AI and IoT-based PBL.

Data Analysis, to determine the statistical significance of observed differences between pre-test and post-test scores, the Pearson's Chi-Square (χ^2) test was applied. This statistical method, widely used in educational research, assesses whether improvements in student motivation, content knowledge, and practical skills are statistically significant [32].

According to the theory presented in the book by Seredenko [33], the chi-square criterion is calculated using Eq. (1).

$$\chi^2 = \sum(Э - T_{кр})^2 / T_{кр} \quad (1)$$

where Э-represents the empirical frequency, and $T_{кр}$ is the critical theoretical frequency. To determine the critical value, it is necessary to calculate the degrees of freedom using the Eq. (2).

$$d_f = (R - 1) \times (C - 1) \quad (2)$$

where R is the number of rows in the table and C is the number of columns [34].

As applied in prior research Bagheri *et al.* [22], Johnson *et al.* [30] Pearson's Chi-Square test was performed separately for each learning component to compare pre-test and post-test distributions. The statistical significance threshold was set at $p < 0.05$, meaning that if the calculated χ^2 value exceeded the critical value, the null Hypothesis (H_0)—which posited that there would be no significant difference between pre-test and post-test results—would be rejected.

IV. Result and Discussion

The application of the chi-square criterion serves as the primary method for aligning empirical data with theoretical models. Eq. (1) is used in analyzing the significance of differences in motivation, content knowledge, and practical skills between the control and experimental groups. As a well-established statistical approach in psychological and pedagogical research, it plays a vital role in the analytical framework used in this study. The authors regard this method as a reliable instrument that enhances the depth and accuracy of analysis, facilitating a structured comparison between expected and observed outcomes.

Theoretically, it was anticipated that the frequencies would be evenly distributed, meaning that values would be proportionally allocated across both groups. To validate this assumption, a theoretical frequency table was generated by multiplying the row totals by the column totals and then dividing the product by the overall sample size (n) (refer to Tables 5–7 and Fig. 5 on the following page).

The categorization of learning outcomes into low, average, and high levels was determined using score percentiles derived from pre-test and post-test results:

- Low: Scores falling within the 0–69% range of total possible points.
- Average: Scores within the 70–89% range of total possible points.
- High: Scores exceeding 90% of total possible points.

The Pearson's Chi-Square test was employed to evaluate the alignment between empirical and theoretical data. As one of the most widely used statistical methods in psychological and pedagogical research, this criterion is applicable across diverse study areas and varying research contexts, ensuring robust and reliable comparative analysis.

$d_f = (R-1) \times (C-1)$, in the case presented here, the degree of freedom in number.

The result of Eq. (2) is $d_f = (R-1) \times (C-1) = (3-1) \times (3-1) =$

4. The significance level used in this analysis is 0.05.

The critical table shows the value of the chi-square criterion below:

$\chi 2_{cr} = 9.488$.

The importance of control in this case:

$\chi 2_{mot} = 14.95$

$\chi 2_{con} = 10.50$

$\chi 2_{prac} = 12.92$

$\chi 2_{cr} = 9.488$.

Table 5. Results by motivation level: distribution of theoretical frequencies

Groups	Low level	Average level	High level	Total
Control	(99 × 79)/167 = 46.83	(59 × 79)/167 = 27.91	(9 × 79)/167 = 4.26	79
Experiment	(99 × 88)/167 = 52.17	(59 × 88)/167 = 31.09	(9 × 88)/167 = 4.74	88
Total	99	59	9	$n = 167$

Table 6. Results by content level: distribution of theoretical frequencies

Groups	Low level	Average level	High level	Total
Control	(115 × 79)/167 = 54.40	(47 × 79)/167 = 22.23	(5 × 79)/167 = 2.37	79
Experiment	(115 × 88)/167 = 60.60	(47 × 88)/167 = 24.77	(5 × 88)/167 = 2.63	88
Total	115	47	5	$n = 167$

Table 7. Results by practical skills level: distribution of theoretical frequencies

Groups	Low level	Average level	High level	Total
Control	(110 × 79)/167 = 52.04	(51 × 79)/167 = 24.13	(6 × 79)/167 = 2.84	79
Experiment	(110 × 88)/167 = 57.96	(51 × 88)/167 = 26.87	(6 × 88)/167 = 3.16	88
Total	110	51	6	$n = 167$

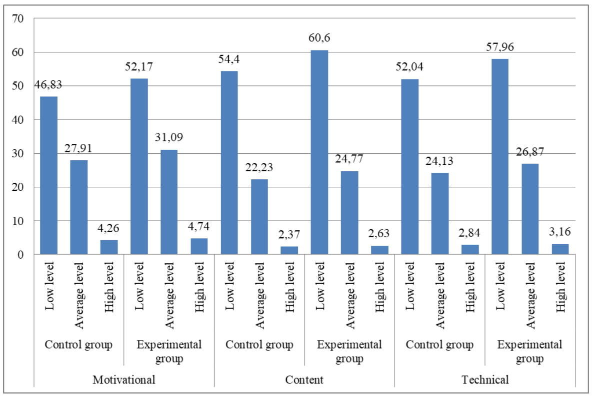


Fig. 5. Diagram of formative experiment results for experimental and control groups.

The findings support the growing body of research that emphasizes the role of AI and IoT in enhancing active learning experiences. Prior studies have highlighted the ability of IoT to personalize and optimize educational processes, reinforcing the effectiveness of integrating AI-driven PBL into STEM curricula [35, 36].

The results indicate a statistically significant improvement in motivation levels among students in the experimental group ($\chi^2 = 14.95$, $p < 0.05$), while the control group showed only minimal changes.These findings are consistent with Pradanna *et al.* [37], who demonstrated that IoT-based adaptive learning environments enhance engagement by providing students with interactive and personalized learning experiences. In addition, these findings are consistent with those of Zawacki-Richter *et al.* [7], who identified a strong correlation between hands-on learning and higher motivation in STEM students. The ability to work on real-world AI-IoT applications appears to increase student interest and enthusiasm for STEM subjects, supporting prior research on technology-driven experiential learning.

Post-test results indicated a significant improvement in content knowledge for the experimental group ($\chi^2 = 10.50$, $p < 0.05$). These findings align with those of Chueapram *et al.* [38], who developed an IoT-based learning kit to improve students' understanding of technical concepts. In addition, Bagheri *et al.* [22], demonstrated that hands-on engagement with real-world AI applications improves comprehension and long-term knowledge retention. Their results demonstrated that hands-on interaction with IoT systems reinforces theoretical knowledge and improves comprehension**.** Similarly, our study confirms that applying AI and IoT concepts through PBL enhances students' understanding beyond what is achieved through traditional instruction.

The experimental group showed significant gains in practical skills ($\chi^2 = 12.92$, $p < 0.05$), indicating that project-based learning fosters problem-solving abilities. This is consistent with Netwong [39], who reported a 13% increase in problem-solving skills following STEM-integrated learning interventions. The improvement in practical skills observed in our study highlights the effectiveness of integrating IoT-based projects into STEM education. Also, this aligns with findings by Nagendrababu *et al.* [40], who identified PBL as a critical factor in enhancing students' technical problem-solving capabilities in engineering disciplines. Furthermore, Meylani [41] emphasized that IoT-driven learning environments offer authentic, real-world contexts that help students apply technical skills and develop industry-relevant competencies. By engaging in real-world AI and IoT applications, students develop technical competencies that prepare them for industry demands.

While differences between pretest and post-test results in the control and experimental groups are expected, this study's key contribution lies in empirically validating. This research extends prior work by Abbasy and Quesada [35], demonstrating that IoT not only enhances digital learning environments but also plays a crucial role in PBL frameworks. The results suggest that incorporating AI-IoT into STEM education can bridge the gap between theoretical learning and real-world applications, providing empirical evidence for curriculum design improvements.

In summary, post-test results strongly support the H_1, indicating that integrating IoT-based projects into STEM education significantly enhances student outcomes. The χ^2 analysis revealed statistically significant improvements in the experimental group in terms of motivation, content knowledge, and practical skills ($p < 0.05$). These findings demonstrate that IoT-based projects foster increased engagement, enhanced learning, and stronger practical competencies, proving their transformative potential in STEM education.

V. Conclusion

This study explored the efficacy of integrating AI and IoT technologies within a PBL framework to advance STEM education at the master's level in Kazakhstan. The results indicate that the experimental group engaged in AI-IoT-driven projects including face recognition, gesture recognition, and speech recognition demonstrated statistically significant improvements in three key domains: motivation, conceptual understanding and practical skills.

The experimental results confirm that students who took part in AI-IoT projects demonstrated greater levels of motivation, a deeper comprehension of concepts, and more strong practical skills than those who followed the traditional lecture-based curriculum. The results were supported by statistical validation through Pearson's chi-square test, which demonstrated the influence of AI-enhanced PBL on learning outcomes.

The research yields several notable contributions to the academic field. First, it provides solid empirical support for the efficacy of integrating AI and IoT in graduate-level STEM education. Second, it offers a model that can be modified for use in a variety of institutional contexts by proposing an organized and reproducible educational framework for AI-IoT-based PBL. Thirdly, by placing the research in the framework of Kazakhstan, this study contributes to the discussion of curriculum modernization in developing educational systems and offers a model for bringing regional curricula into line with international technological demands. All of these observations support the crucial role of experiential learning in cultivating the technical expertise, critical problem-solving abilities, and engagement essential for master's students to thrive in an AI-dominated era.

This investigation lays a solid groundwork for embedding AI and IoT within STEM education and illuminates several pathways for further research to deepen its impact and broaden its applicability. Future studies can pursue the following directions:

Longitudinal Analysis of Outcomes: Through conducting a study spanning multiple years (e.g., 2–5 years) scholars could assess the enduring effects of AI-IoT-based PBL on students' professional careers, skill retention, which would enhance knowledge of sustained educational value.

Cross-Institutional Scalability: Through expanding the application of this framework to a wider array of institutions within Kazakhstan and beyond it would be possible for scholaars to evaluate its scalability and adaptability across varying educational infrastructures, resource availabilities, and cultural contexts.

Advancement through Emerging Technologies: Adding advanced AI techniques, like deep learning architectures, or next-generation IoT hardware could make project designs more complex, bringing them closer to industry advancements and better preparing students for new technological developments.

The proposed directions aim to improve and broaden the current framework by ensuring its applicability and effectiveness in many educational contexts. By addressing these aspects, future research could promote the continuous development of STEM education and provide professionals with evidence based tools to help students get ready for the needs of a technologically advanced future.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Meruert Serik supervised the project, providing guidance on the experimental design and methodology. Kymbat Tleuzhanova conducted the research and designed the IoT-based projects. Symbat Nurgaliyeva analyzed the data and performed the statistical tests. Kymbat Tleuzhanova wrote the paper, and all authors contributed to the revision and final approval of the manuscript. All authors have approved the final version.

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