



ISSN: 2617-6548

URL: www.ijirss.com



Factors of career development of students of technical specialties in the era of artificial intelligence

 Nurbekova Zhanat¹,  Naimanova Dinara²,  Dautova Aigul³,  Ospanova Nazira⁴,  Tkach Galina⁵

¹*Abai Kazakh National Pedagogical University Republic of Kazakhstan.*

^{2,3,4,5}*Faculty of Computer Science Toraihyrov University Pavlodar, Republic of Kazakhstan.*

Corresponding author: Hotma Harapan Saragih (Email: nurbekova_zhk@digitalexgroup.com)

Abstract

Based on the analysis of the competencies imposed by universities on graduates, as well as the requirements put forward by employers in the era of rapid development of technology and artificial intelligence, this article presents the results of a study dedicated to modeling the career trajectories of students of technical specialties. The modern labor market requires young specialists not only to have deep theoretical training but also practical skills that allow them to effectively adapt to rapidly changing conditions and technologies. As part of the study, a comprehensive assessment of educational courses implemented at universities was carried out in terms of their compliance with the current needs of employers. Based on the study, a number of recommendations have been formed for the modernization of the content of educational programs, including the introduction of interdisciplinary modules, the expansion of cooperation with employers, as well as the strengthening of the project and research components of courses, that is, participation in internships, hackathons, etc., knowledge economy, industry, and taking into account the development of the era of artificial intelligence. The emphasis is also placed on identifying the factors of career development of students of technical specialties in the era of artificial intelligence, based on the analysis of the competencies of educational programs of graduates of technical specialties and the analysis of the labor market. With the rapid automation and adoption of AI, such approaches give students the opportunity to develop skills in adaptive thinking, big data analysis, teamwork, and independent decision-making. The importance of integrating cases from real practice, internships, and mentoring by representatives of the IT industry into the educational process is emphasized.

Keywords: Artificial intelligence, Career development factors, Competency analysis, IT vendors, Employer, Labor market, Modeling, Academic performance, Professional skills, Technical specialties.

DOI: 10.53894/ijirss.v8i6.9505

Funding: This work is supported by the Committee of Science of the Ministry of Science and Higher Education of the Republic of Kazakhstan (Grant number: AP23489805).

History: Received: 23 June 2025 / **Revised:** 25 July 2025 / **Accepted:** 28 July 2025 / **Published:** 27 August 2025

Copyright: © 2025 by the authors. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license (<https://creativecommons.org/licenses/by/4.0/>).

Competing Interests: The authors declare that they have no competing interests.

Authors' Contributions: All authors contributed equally to the conception and design of the study. All authors have read and agreed to the published version of the manuscript.

Transparency: The authors confirm that the manuscript is an honest, accurate, and transparent account of the study; that no vital features of the study have been omitted; and that any discrepancies from the study as planned have been explained. This study followed all ethical practices during writing.

Publisher: Innovative Research Publishing

1. Introduction

At present, there is a trend of interaction between educational institutions and employers. Since the modern labor market requires graduates of technical specialties not only to have deep knowledge in their professional field but also to develop practical skills that meet the needs of employers, a set of personal qualities such as the ability to work in a team, soft skills, communication, the ability to work in multitasking mode, and competent oral and written speech remain relevant. Their competitiveness in the labor market also remains significant.

At the moment, as a result of the analysis of modular training programs and vacancies on popular platforms, it shows that there is a discrepancy between the competencies of graduates and the expectations of employers. Due to the rapidly changing rhythm of life and progress in the IT sector, as well as the personal qualities that a graduate of technical specialties should possess.

2. Literature Review and Problem Statement

The modern labor market in the field of technical specialties is rapidly transforming under the influence of digitalization, the development of IT infrastructure, and the growth of employers' requirements.

The issue of predicting academic performance in higher education institutions plays a key role in the field of education system analytics and helps in solving the problem of personalization of learning. Within the framework of the study, an analysis of a large number of studies devoted to this issue was carried out. Rafiq et al. [1] confirm the relevance of studying this issue and consider methods of data analysis to improve the accuracy of predictions [1], and Liang et al. [2] propose to apply a hierarchical model for predicting academic performance, emphasizing the complexity of choosing a career due to the variety of available options Liang et al. [2]. Mahboob et al. [3] explore an intelligent career path forecasting system, recommending that academic performance, CGPA, projects, and demographic factors be taken into account Mahboob et al. [3]. Folorunso et al. [4] confirm the importance of machine learning in educational analytics by proposing a hybrid method for assessing academic performance Folorunso et al. [4]. Zhang et al. [5] analyze methods for predicting academic achievement, but do not touch on the relationship with career development Zhang et al. [5]. Ogundele et al. [6] in their study identified such a factor as the influence of attendance and the learning environment on academic results Ogundele et al. [6]. Loncarevic et al. [7] apply hidden Markov models to predict the dynamics of academic success, which can contribute to personalized student support [7]. In addition to the factors discussed above, personal and cognitive factors also play an important role in the successful learning of students. Bhoomika et al. [8] use the OCEAN model and cognitive tests, showing that personality traits can predict academic performance Bhoomika et al. [8]. Gupta and Varade [9] confirm the effectiveness of neural network methods [9], and Thamilselvan et al. [10] emphasize the influence of sociodemographic factors, stress, and lifestyle on academic performance, identifying the key determinants of success Thamilselvan et al. [10]. Wijayaningrum et al. [11] investigate the problem of unbalanced data in predicting academic performance using the SMOTE method and multilayer perceptron (MLP), achieving high predictive accuracy Wijayaningrum et al. [11]. Novo [12] in their study considered the use of data mining to predict academic performance, revealing the significance of the Naïve Bayes algorithm [12].

Internships have a significant impact on the career development of students. Siregar et al. [13] show that educational internships develop practical and analytical skills, interpersonal communication, and adaptability Siregar et al. [13]. Ferraz [14] in his research highlights the importance of internships in developing transversal skills and preparing for market demands in an AI environment. The study confirms that professional continuity before the pandemic contributes to adaptation to crisis situations, and students demonstrate a high level of social and professional adaptation despite the challenges Ferraz [14]. Savelieva [15] notes that competitive activities, including engineering championships, contribute to professional development, forming practical experience and entrepreneurial thinking Savelieva [15]. Pardo Regueiro et al. [16] analyze the impact of scientific competitions on the development of engineering competencies, including modeling and teamwork [16]. Scientific activity also plays a key role in professional development. Alipina and Kitapbayeva [17] prove that research competencies contribute to critical thinking, intellectual activity and readiness for high-tech tasks, which is especially important in the context of digital transformation Alipina and Kitapbayeva [17]. Balcioglu and Artar [18] investigate the effectiveness of machine learning models to identify at-risk students, showing the advantage of ensemble models Balcioglu and Artar [18]. Iwasokun et al. [19] apply a neuro-fuzzy model to predict student performance,

providing flexibility in decision-making [19]. A study by Sousa et al. [20] analyzes the role of internship practices in the formation of teachers' professional competencies, emphasizing the importance of integrating practical experience into educational programs [20].

Thus, academic achievements, practical experience, participation in competitions, and research activities form the professional development of students, helping them adapt to the requirements of the labor market in the era of artificial intelligence.

In the era of AI, there is a significant transformation of career strategies needed to adapt to the new demands of the labor market. Rachma et al. [21] explore career development strategies in human resource management (HR), highlighting the impact of automation and digital technologies on professional growth Rachma et al. [21]. Badulescu et al. [22] consider AI-related competencies required for the labor market and business. The study is based on the PLS-SEM approach and demonstrates the importance of adapting educational programs to the new conditions of the digital economy Badulescu et al. [22]. Miao and Yao [23] explore the professional development of educators in the age of AI, highlighting the need to rethink their roles and develop new educational approaches Miao and Yao [23]. Chatterjee [24] assesses the impact of AI-based training programs on skills development and career development, revealing that personalized educational technologies can significantly improve the level of training of specialists Chatterjee [24]. Kumar, et al. [25] analyze the impact of AI on employment and jobs in India, identifying the risks of automation and the need to reskill employees to remain competitive Kumar et al. [25]. Chauhan et al. [26] discuss the need for retraining in the context of active AI implementation, focusing on changing professional competencies and approaches to training Chauhan et al. [26]. Jing et al. [27] apply system dynamics to analyze the factors affecting the training of AI professionals. They identify key variables such as technological infrastructure, educational initiatives, and personnel policies Jing et al. [27]. Călinescu and Tanaşciuc [28] examine the changing skills requirements in the labor market in the context of AI development, using Finnish universities as an example. They emphasize the importance of integrating interdisciplinary knowledge and flexibility in education, Călinescu and Tanaşciuc [28]. Ullah et al. [29] conducted a systematic review of the impact of AI on workflows and workforce transformation in the context of the Fourth Industrial Revolution, demonstrating that digitalization necessitates a revision of recruitment and training strategies [29].

In general, the following recommendations can be formulated based on the analysis, which are important for professional development in the era of AI. One of the most important factors is the *development of adaptive educational programs*. Education professionals need to integrate AI-related skills into educational programs, including courses in machine learning, data analytics, and automated systems. Such a factor as the *flexibility of career strategies for automating work processes* requires specialists to constantly update their knowledge and adapt to new technological realities. It is important to take into account *the professional development of teachers*. In this regard, it is necessary to implement strategies for retraining and professional development of teachers for the effective use of AI in the educational process, research projects, and educational programs focused on training specialists in the field of AI. The formation of new career strategies in the era of AI requires a comprehensive approach, including the adaptation of educational programs, the development of teaching competencies, and the creation of personalized learning models.

The development of digitalization and the widespread introduction of artificial intelligence technologies have a significant impact on changes in the economy, the labor market, and the education system. This leads to the fact that the previously used traditional approaches to training technical specialists have become irrelevant. If earlier the emphasis was mainly on narrow-profile knowledge and technical skills, today this is no longer sufficient for a successful career. Many students of technical specialties face difficulties in building a professional trajectory: uncertainty in the choice of development direction, lack of knowledge about the requirements of the modern labor market, lack of self-presentation skills, and project activities. At the same time, the accelerating pace of technological change reinforces the need for adaptability, continuous learning, and the development of both digital and interpersonal competencies. In this regard, there is a need to identify and analyze the key factors that determine the success of the career development of students of technical specialties in the context of the spread of AI. This will make it possible to adjust educational programs in a timely manner, form relevant competencies, and promote the professional self-realization of young specialists.

3. The Aim and Objectives of the Study

The purpose of the study is to identify the factors influencing the career development of students in technical specialties in the era of artificial intelligence based on the analysis of the competencies of educational programs of graduates of technical specialties and the analysis of the labor market (based on the requirements imposed by employers on information platforms enbek.kz, hh.kz, Rabota.kz, linkedin.com).

Research questions:

1. What academic achievements and skills of students of technical specialties and the requirements of the labor market, affect their career trajectory?
2. What are the key factors influencing professional formation and professional development in the age of AI?
3. What are the basic recommendations for the professional development of students of technical specialties in the era of AI?

Modern research emphasizes the importance of a multidimensional approach to predicting academic performance. Rafiq et al. [1] proposed a model based on machine learning that considers the demographic, social, emotional, and cognitive characteristics of learners. Such a model not only accurately predicts students' success but also tracks the development of their competencies, which is especially important for technical specialties where a high level of adaptability and analytical thinking is required. Rafiq et al. [1]. Folorunso et al. [4] applied a hybrid model based on linear

regression and k-means clustering algorithms, identifying significant parameters of students' academic behavior and highlighting the potential for early identification of problem areas for subsequent pedagogical intervention [4]. In a number of works, special attention is paid to the personal and cognitive characteristics of students. A study by Bhoomika et al. [8] based on the OCEAN model and cognitive tests it has confirmed that individual characteristics play an important role in students' academic success and, consequently, in the development of their professional potential [8]. The career trajectory of students in technical specialties is influenced by a combination of academic achievements and personal characteristics. Primarily, the overall level of academic performance, including grades in specialized disciplines, grade point average (GPA), and results of final projects that reflect the development of key competencies, is a significant factor. Cognitive abilities—such as intellectual development, logical thinking, and problem-solving—play an important role, as confirmed by research based on cognitive tests and personality models like OCEAN. Personality traits, including conscientiousness, openness to new experiences, and emotional stability, contribute to successful learning and professional adaptation. Additionally, social-emotional skills, such as cooperation, self-organization, and emotional regulation, are crucial. Models considering these parameters demonstrate high accuracy in predicting students' readiness for professional activity. Of particular importance is the ability to self-develop and early identify problem areas in learning, which enables students to adapt to educational and professional challenges. Therefore, a successful professional trajectory is built not only on academic achievements but also on developed cognitive, personal, and adaptive skills necessary for effective work in the digital economy and the rapid integration of artificial intelligence technologies.

The development of AI and intelligent systems is changing the requirements for future professionals, emphasizing the need not only for academic training but also for soft skills, digital literacy, and the ability to learn continuously. Gupta and Varade [9] demonstrated the effectiveness of a hybrid approach combining artificial neural networks and particle swarm optimization in predicting academic success. This approach can serve as an indicator of students' professional stability in a rapidly changing technological environment [9]. At the same time, Miao and Yao [23] emphasize the limitations of existing models focused solely on academic metrics and the need for further research linking academic achievement with successful professional realization [23]. In the era of rapid development of artificial intelligence technologies, the professional formation and development of specialists, particularly in technical fields, are determined by several key factors. First, soft skills, including critical thinking, complex problem-solving, communication, and teamwork, are of particular importance. These skills enable individuals to adapt to a rapidly changing work environment, where automation requires not just knowledge but also the ability to utilize technology to create new solutions. The second important factor is digital literacy — mastery of modern digital tools, understanding the principles of AI, and the ability to work with large datasets and employ analytics methods. Such competencies form the foundation for successful professional implementation across most industries. Equally important is the readiness for continuous learning. The rapid obsolescence of knowledge in the context of technological progress necessitates that specialists constantly update their skills and learn new approaches and tools. This involves developing meta-skills such as self-learning, reflection, and managing one's educational trajectories. Additionally, in the context of AI, the role of an interdisciplinary approach is increasing, i.e., the ability to integrate knowledge from different fields, which is especially crucial for creating innovative solutions. Finally, personal stability, including emotional intelligence, stress resistance, and intrinsic motivation, is vital. These qualities help individuals cope with uncertainty and high levels of competition in the labor market.

4. Materials and Methods

The study utilized materials and methods including surveys and interviews with IT students and employers from IT companies. Analysis through descriptive statistics, factor analysis, and qualitative processing of interviews has demonstrated that, in the context of rapid technological progress, personalized approaches to predicting career trajectories are particularly important. These approaches consider not only students' academic performance but also their professional skills, participation in projects, internships, and labor market trends. An analysis of vacancies and monitoring of educational programs reveal a gap between graduates' competencies and employers' expectations. This discrepancy leads to decreased competitiveness among young specialists and complicates their employment and career development.

The study utilized data from modular training programs listed in the register of educational programs, available on the unified platform of higher education of the Republic of Kazakhstan - epvo.kz. For the specialties under consideration, the survey sample comprised 50 students in the 3rd and 4th years of technical specialties (questionnaire) and 20 employers from the IT sector (questionnaire).

We have selected statistical methods, correlation analysis, and clustering as analytical tools. We chose the correlation-regression method and the principal component method to study the impact of various factors on career growth success.

In our case, the choice was made to use the correlation-regression method, which is a statistical approach to analyze the relationship between variables. It allows us to determine how much and in what direction one variable will change when another changes. This method is useful when assessing the strength of the relationship between graduates' competencies and employers' requirements, as well as to determine the impact of various factors (e.g., type of course, practice, skills) on career success.

The development of a model for forecasting the career growth of graduates, based on the analysis of competencies and employer requirements, enables the optimization of educational programs considering current market demands. It promotes more effective professional development for students, improves the system of career guidance and support for graduates, and increases the employment level of specialists in technical fields. Therefore, this study aims to create effective tools for forecasting and adapting graduates to the modern labor market, which is a crucial task in the context of higher education development and sustainable economic growth.

Our analysis is based on data regarding competencies included in the educational programs of universities in Kazakhstan: Abai Kazakh National Pedagogical University, L.N. Gumilyov Eurasian National University, Al-Farabi Kazakh National University, Toraigyrov University, Kazakh-British Technical University, International IT University, Suleyman Demirel University, Astana IT University, and studied training programs at foreign universities: Massachusetts Institute of Technology, USA, Arizona State University, USA, SRH Heidelberg, Germany, Technische Universität München, Germany, University of Essex, Great Britain, University of Leeds, Great Britain, Dundalk IT, Ireland.

Table 1.

Matrix of Basic Competencies in Educational Programs in the Specialties "Information Systems", "Computer Science", and "Computer Science" of Universities.

| Competencies/ learning outcomes | Name of the university | | | | | | | |
|------------------------------------|---|--|--|-------------------------------------|-----------------------------|-----------------------------|----------------------|-----------------------|
| | Abai Kazakh National Pedagogical University | Kazakh National University named after Al-Farabi | L.N. Gumilyov Eurasian National University | Kazakh-British Technical University | International IT University | Suleyman Demirel University | Astana IT University | Toraigyrov University |
| Competence 1 | + | - | - | - | - | + | + | - |
| Competence 2 | + | - | - | - | - | - | - | - |
| Competence 3 | + | + | + | + | + | + | - | + |
| Competence 4 | + | - | - | + | - | - | - | - |
| Competence 5 | - | + | - | - | - | + | - | + |
| Competence 6 | - | + | - | - | - | - | - | - |
| Competence 7 | - | + | - | - | - | - | - | + |
| Competence 8 | - | + | - | - | - | - | - | - |
| Competence 9 | - | + | - | - | - | - | - | + |
| Competence 10 | - | - | + | - | - | + | + | - |
| Competence 11 | + | - | + | - | + | + | + | + |
| Competence 12 | - | - | + | - | - | + | + | - |
| Competence 13 | + | + | + | - | - | + | + | + |
| Competence 14 | - | - | - | + | - | - | - | - |
| Competence 15 | - | - | - | - | + | - | - | - |
| Competence 16 | - | - | - | - | + | - | + | - |

Competency 1: Possess the ability to design basic and applied information technologies; the ability to generate new competitive ideas and implement them in projects.

Competency 2: Use digital tools and methods to conduct pedagogical research; apply theoretical and experimental results in solving practical problems and evaluate their reliability.

Competency 3: Analyzes basic knowledge to solve practical problems in the field of information systems and technologies; applies modern computer technologies for information retrieval to solve problems, critically analyzes this information, and evaluates the substantiation of the adopted ideas and approaches to the solution.

Competence 4: to apply methods and means of cognition, learning, and self-control for intellectual development, raising the cultural level, and professional competence.

Competence 5: Install and use system and application software on various platforms, and manage system resources to support the informatization of the enterprise.

Competency 6: Develop and modernize IP components using different programming approaches and technologies.

Competency 7: Design the components of information systems and their interrelations using modeling and design technologies.

Competency 8: Use data mining algorithms and tools to extract information for effective decision-making.

Competency 9: Manage information systems security and data protection using information security software and hardware.

Competence 10: Use digital technologies, various types of information and communication technologies to search, store, process, protect, and disseminate information.

Competence 11: Software development, selection of standards, methods, and tools of programming languages for software development, application of the basic principles of software design, development and documentation of software interfaces and databases, description of software components.

Competence 12: Organize big data processing, provide big data storage, create data processing software, determine data criteria for data search and extraction, apply methods for developing SQL queries, use methods for fast data search and processing, and work with various technologies such as neural networks.

Competency 13: Install and configure server operating systems and workstations for both Windows and Linux. Manage data warehouses. Configure network services. Plan and implement server deployment infrastructure. Develop and manage IP address management (IPAM) solutions. Install web servers.

Competency 14: Develop the ability to self-learn, identify current trends and tendencies, and use a variety of techniques, skills, and modern engineering tools for research activities.

Competence 15: to use software, hardware, information, mathematical, and functional support of information systems for software modernization, formation of sections of technical specifications for the design of IT infrastructure, improvement of program modules, data processing for automated systems, design and development of front-end and back-end web resources, and description of information and mathematical models.

Competence 16: To develop information systems and their components across various subject areas to address practical scientific and technical problems using modern ICT and IT project management methods, incorporating modern technologies such as 3D modeling, IoT, VR/AR technologies, and others as tools.

In the context of the active introduction of AI technologies, universities in Kazakhstan are taking steps to update educational programs, taking into account the changing requirements of the labor market. An analysis of the curricula of disciplines in a number of Kazakh universities shows the presence of positive dynamics in the formation of key competencies. Among the most relevant competencies that are formed in the learning process are the following: the basics of programming and algorithmization, basic cybersecurity and digital hygiene skills, the use of modern IT tools and digital platforms, work in virtual and mixed environments, data analysis, machine learning, the basics of artificial intelligence, project activities and teamwork, critical thinking and the ability to solve non-standard problems, the ability to self-learn and self-regulate, interdisciplinary thinking and a systematic approach, the ability to self-learn and self-regulation.

At the same time, it should be noted that despite the presence of trends toward updating, challenges remain: unevenness in the quality of training by region, insufficient integration of AI into training courses, and limited opportunities for students' project and research activities.

Thus, universities in Kazakhstan are at the stage of active transformation of the content of education; a systematic approach is required for the effective formation of the competencies necessary for the era of AI.

Table 2.
Key competencies of top universities.

| University | Program | Key competencies |
|---|----------------------------------|---|
| Massachusetts Institute of Technology (MIT) | Computer Science and Engineering | Algorithms and Data Structures, Software Development, Artificial Intelligence, Cybersecurity, Big Data, Programming Language Skills (C++, Python, Java) |
| Arizona State University | Computer Science | Algorithms and data structures, Software development, Artificial Intelligence and Machine Learning, Operating System Fundamentals, Computational Theory, Working with Programming Languages, Cybersecurity and Cryptography, Critical Thinking and Problem Solving, Communication and Teamwork, Project Management, and the Ability to Learn and Adapt. |
| Technische Universität München (TUM) | Informatics | Algorithms and Data Structures, Programming in Python, C++, Java, Software Development, and Testing. Agile/Scrum project management, network administration and distributed systems development, information systems security, intelligent systems development and applications, legal and social understanding in technology development, learning and using machine learning models, implementing solutions to real-world business problems, critical thinking and problem solving, innovation and research ability, effective work in interdisciplinary and international teams, high level of technical training and English language proficiency, adaptation to technological changes and modern challenges. |
| University of Essex | Computer Science | Confident command of programming languages (Python, Java, C++). Design and optimization of algorithms. Working with large |

| University | Program | Key competencies |
|---------------------|--|---|
| | | <p>amounts of data. Knowledge of operating systems, virtualization, and computer architecture. Fundamentals of machine learning and deep learning. Working with neural networks and libraries (TensorFlow, PyTorch). Data protection and cryptography. Analyze threats and develop secure systems. Ability to work in teams using Agile/Scrum. Awareness of the legal and ethical aspects of technology development. Critical thinking and problem solving. Effective communication and teamwork. Adaptation to new technologies and trends. Scientific research and analytical skills. Understanding the global IT landscape and its requirements.</p> |
| University of Leeds | <p>Computer Science and Mathematics, Computer Science with Artificial Intelligence, Computer Science with High-Performance Computing</p> | <p>Knowledge of programming languages: Python, Java, C++, C#, JavaScript. In-depth understanding of algorithms and data structures. Knowledge of artificial intelligence, machine learning, and data analysis. Ability to work with graphics and game engines (Unity, Unreal Engine). Experience with high-performance computing (HPC) systems. Knowledge of cybersecurity and data protection principles. Ability to solve complex problems and develop effective algorithms. Big data analysis using Data Science tools (R, SQL, Pandas). Ability to work in a team and communicate effectively. Project management skills. Ability to adapt to new technologies. Participation in hackathons, open projects, or internships. Creating a portfolio of real-world projects (e.g., game development, data visualization, or AI applications).</p> |
| Dundalk IT | <p>Augmented and Virtual Reality, Computing in Games Development, Computing in Software Development, Computing</p> | <p>Knowledge of programming languages: Python, Java, C++, C#, JavaScript. Knowledge of game development and game engines (Unity, Unreal Engine). Skills in working with 3D graphics and animation. Knowledge of the basics of virtual and augmented reality, including relevant APIs (ARKit, ARCore, OpenXR). Ability to design and develop software using modern frameworks (React, Spring, Django). Fundamentals of cybersecurity. Work with databases (SQL, NoSQL). Cloud technologies (AWS, Azure, Google Cloud). Code and performance optimization for games and VR/AR applications. Algorithms and data structures. Mathematics for graphics: linear algebra, vector mathematics, 3D transformations. Statistics and data analysis. Ability to develop user interfaces (UI/UX). Visual design and design of game or VR/AR experiences. Creative thinking to develop a unique user experience. Teamwork skills. Project management. Ability to self-learn and adapt to new technologies.</p> |

The competencies and skills of MIT students often exceed the expectations of IT vendors due to their focus on innovation, research, and knowledge integration across various disciplines. At the Massachusetts Institute of Technology (MIT), each IT program includes a unique set of disciplines designed to equip students with the necessary knowledge and skills for a successful career. Technische Universität München (TUM) University emphasizes practical teaching, scientific research, and project work in collaboration with leading companies and scientific organizations. The University of Essex in the UK offers a variety of IT-related programs, each focusing on different aspects of the industry. Let's examine the key requirements of IT vendors and the disciplines typically studied in these programs. The University of Leeds in the UK provides IT programs focused on various facets of computer technology, from artificial intelligence to game engineering. To become competitive in the labor market, students need to develop a broad range of competencies. Dundalk Institute of Technology (Dundalk IT) in Ireland offers programs aimed at training IT professionals in virtual reality, game

development, software, and computing technologies. Foreign universities demonstrate a systematic approach to developing digital and technical competencies essential for a successful career in the era of AI.

5. Results

The modern labor market in the field of technical specialties is rapidly transforming under the influence of digitalization, the development of IT infrastructure, and the growth of employers' requirements. As a result of the research, groups of factors were identified: educational (quality of programs, access to projects), personal (purposefulness, responsibility), and digital (knowledge of programming languages).

The table systematizes data on the list of key competencies formed in the curricula of technical specialties at leading Kazakhstani and foreign universities. The table allows tracking of overlapping competencies.

This comparison aims to identify the factors influencing the career development of students in technical specialties in the era of AI. The table reveals the academic achievements and skills developed in universities and how they correlate with the requirements of the global labor market.

In addition, the analyzed data makes it possible to assess which key institutional and personal factors, such as participation in projects, internships, the development of soft skills, and digital literacy, contribute to the professional formation and development of students. The table serves as a tool for visualizing the comparison of educational practices and market expectations and is also the basis for further recommendations for modernizing the content of technical education in Kazakhstan.

Table 3.

Matrix of basic competencies in educational programs in the specialties "Information Systems", "Computer Science", and "Computer Science" of top universities.

| Competence/ learning outcomes | Name of the university | | | | | | | | | | | | | |
|----------------------------------|---|--|--|-------------------------------------|-----------------------------|-----------------------------|----------------------|------------------------|---|--------------------------|--------------------------------------|---------------------|---------------------|------------|
| | Abai Kazakh National Pedagogical University | Kazakh National University named after Al-Farabi | L.N. Gumilyov Eurasian National University | Kazakh-British Technical University | International IT University | Suleyman Demirel University | Astana IT University | Toraighyrov University | Massachusetts Institute of Technology (MIT) | Arizona State University | Technische Universität München (TUM) | University of Essex | University of Leeds | Dundalk IT |
| Competence 1 | + | - | - | - | - | + | + | - | - | + | + | + | + | + |
| Competence 2 | + | - | - | - | - | - | - | - | - | - | - | - | - | - |
| Competence 3 | + | + | + | + | + | + | - | + | - | - | + | - | + | - |
| Competence 4 | + | - | - | + | - | - | - | - | - | - | - | - | - | - |
| Competence 5 | - | + | - | - | - | + | - | + | - | + | + | + | + | - |
| Competence 6 | - | + | - | - | - | - | - | - | - | - | - | - | - | - |
| Competence 7 | - | + | - | - | - | - | - | + | - | - | - | + | - | + |
| Competence 8 | - | + | - | - | - | - | - | - | - | - | - | - | + | + |
| Competence 9 | - | + | - | - | - | - | - | + | + | + | + | + | + | - |
| Competence 10 | - | - | + | - | - | + | + | - | - | - | - | - | - | - |
| Competence 11 | + | - | + | - | + | + | + | + | + | + | + | + | + | + |
| Competence 12 | - | - | + | - | - | + | + | - | + | + | + | + | + | + |
| Competence 13 | + | + | + | - | - | + | + | + | - | - | - | - | - | + |
| Competence 14 | - | - | - | + | - | - | - | - | - | - | + | + | - | - |
| Competence 15 | - | - | - | - | + | - | - | - | - | - | - | - | - | - |
| Competence 16 | - | - | - | - | + | - | + | - | - | - | - | - | - | + |

Competency Overlaps Between All Universities

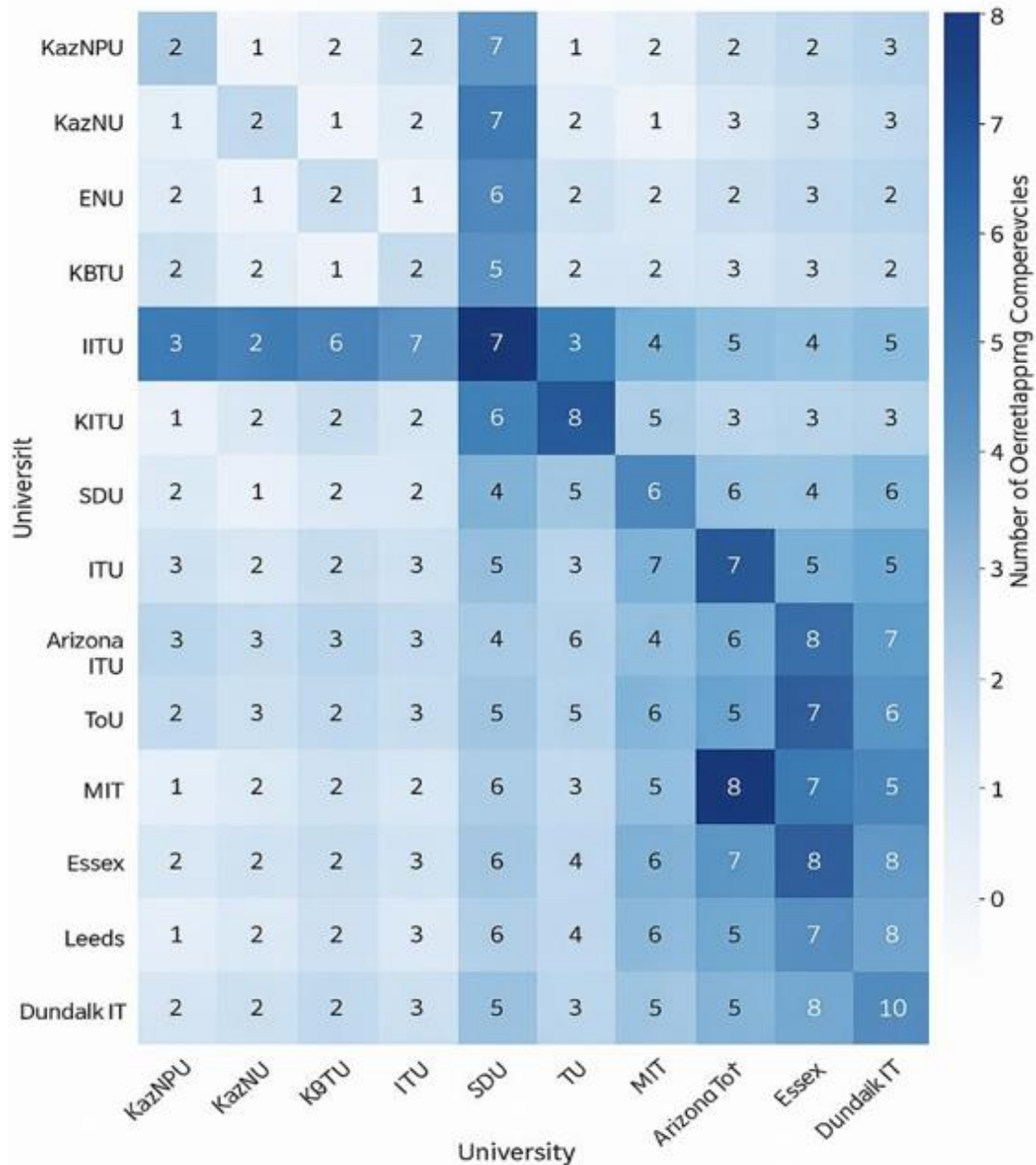


Figure 1. Matrix of basic competencies of selected universities.

The diagram presented in Figure 1 shows which pairs of universities have the most overlap in competencies. This indicates similar educational programs or methodological approaches in these universities. With the least degree of overlap in competence, we can understand this as the fact that the programs of this university are more specialized or focused on other priorities.

An analysis of the competencies of Kazakhstani universities showed that a graduate of IT specialties should easily adapt to changing environmental conditions and make management decisions in situations of disagreement. They should be able to use digital technologies and various types of information and communication technologies to search, store, process, protect, and disseminate information, as well as apply entrepreneurial knowledge in various fields of activity. Graduates should also be able to apply the mathematical apparatus and physical principles of operation of the main electronic devices in solving professional problems. They should be capable of describing the architecture and principles of organization of multiprocessor and multimachine computing systems, mastering the basic concepts of system programming, and justifying the choice of architecture for modern computers, systems, and networks. Additionally, they should develop programs using API functions, apply system security mechanisms built into the OS, and perform system administration. Graduates should be able to select optimal data structures by developing algorithms and implementing them in programming languages,

debug, analyze source code, and prepare reporting documentation. They should also be able to set up and configure programmable logic controllers and microprocessor systems, and develop control programs for robotic and embedded systems. Furthermore, they should apply theoretical knowledge, practical skills, and a creative approach in developing modern interactive intelligent applications and databases, realize the synthesis of stereoscopic images using tracking technology and game engines, and apply programming technologies to ensure software multitasking. Graduates should develop and use hardware and software tools for error correction in data transmission and processing in telecommunications systems, utilizing cryptographic primitives and assessing security threats associated with attacks on cryptographic protection methods. They should possess basic theoretical and practical knowledge in the field of computer engineering and software, as well as manage IT projects. Finally, they should be capable of implementing system and application software that ensures the functioning and deployment of information systems.

An analysis of vacancies on popular platforms (Enbek.kz, hh.kz, Rabota.kz, linkedin.com) shows the main requirements of employers for potential employees in technical specialties:

The required work experience ranges from 3 to 6 years, including Windows and Linux administration. The ability to multitask, strong communication skills, competent oral and written speech, as well as the ability to interact effectively within a team, are important. You must confidently diagnose problems with operating systems, software, and hardware components. Knowledge of network protocols (LAN, NAT, DNS) and practical experience in network administration, along with a thorough understanding of network technologies and IT security, are essential. All these requirements can be conditionally divided into internal and external factors.

Internal factors include: educational program, student involvement in projects with real companies, teamwork, communication (soft skills).

External factors include: knowledge in the field of cloud DevOps technologies, competition among novice specialists with no work experience, and a lack of internships from the employer.

Table 4.
Requirements of employers of popular platforms for the provision of vacancies.

| Employers' requirements | Popular Platforms | | | |
|---|---------------------------|----------|-----------|--------------|
| | Headhanter (www.hh.kz) | Enbek.kz | Rabota.kz | linkedin.com |
| Strong command of programming languages | + | + | + | + |
| Knowledge in the field of administration of system and application software, databases, server equipment, Windows, and network protocols. | + | + | + | + |
| At least 3 years of experience in the field of IT | + | - | + | - |
| Knowledge of how network protocols work (LAN, NAT, DNS) | + | + | + | + |
| Higher education with appropriate qualifications | + | + | + | + |
| Ability to multitask, high communication skills | + | + | + | + |
| Experience in collective software development, teamwork, and communication (soft skills). | + | + | + | + |

Thus, the analysis of competencies formed in Kazakhstani and foreign universities, as well as an overview of current vacancies on popular employment platforms, showed that the requirements for young IT specialists are becoming increasingly complex. Graduates are expected not only to have a high level of technical training, including knowledge in the fields of programming, AI, and cloud technologies, but also to develop soft skills: the ability to work in a team, communicate, adapt, and learn throughout life. Foreign universities demonstrate a systematic approach to the formation of such competencies, while Kazakhstani educational institutions will need to intensify the integration of project-based learning and interaction with industry.

6. Discussion of Results

Leading IT vendors such as Google, Microsoft, and Amazon are increasingly focusing not only on the technical training of future specialists but also on the comprehensive development of their digital and interdisciplinary competencies. Modern requirements include a strong command of programming languages, big data, and AI skills, as well as the ability to think critically, self-learn, communicate, and work in teams. All this requires a rethinking of approaches to training in universities and updating educational programs, taking into account the needs of the global digital market. Figure 2 shows external and internal requirements for the career readiness of students in the digital market.

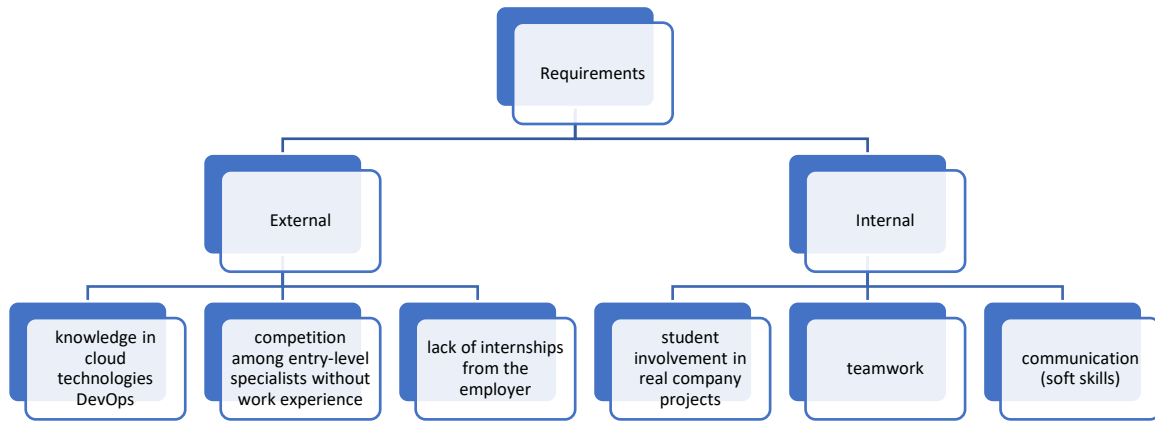


Figure 2.
External and internal requirements for the career readiness of students in the digital market.

Figure 3 shows the competencies and skills of MIT students often exceed the expectations of IT vendors due to their focus on innovation, research, and knowledge integration in various disciplines.

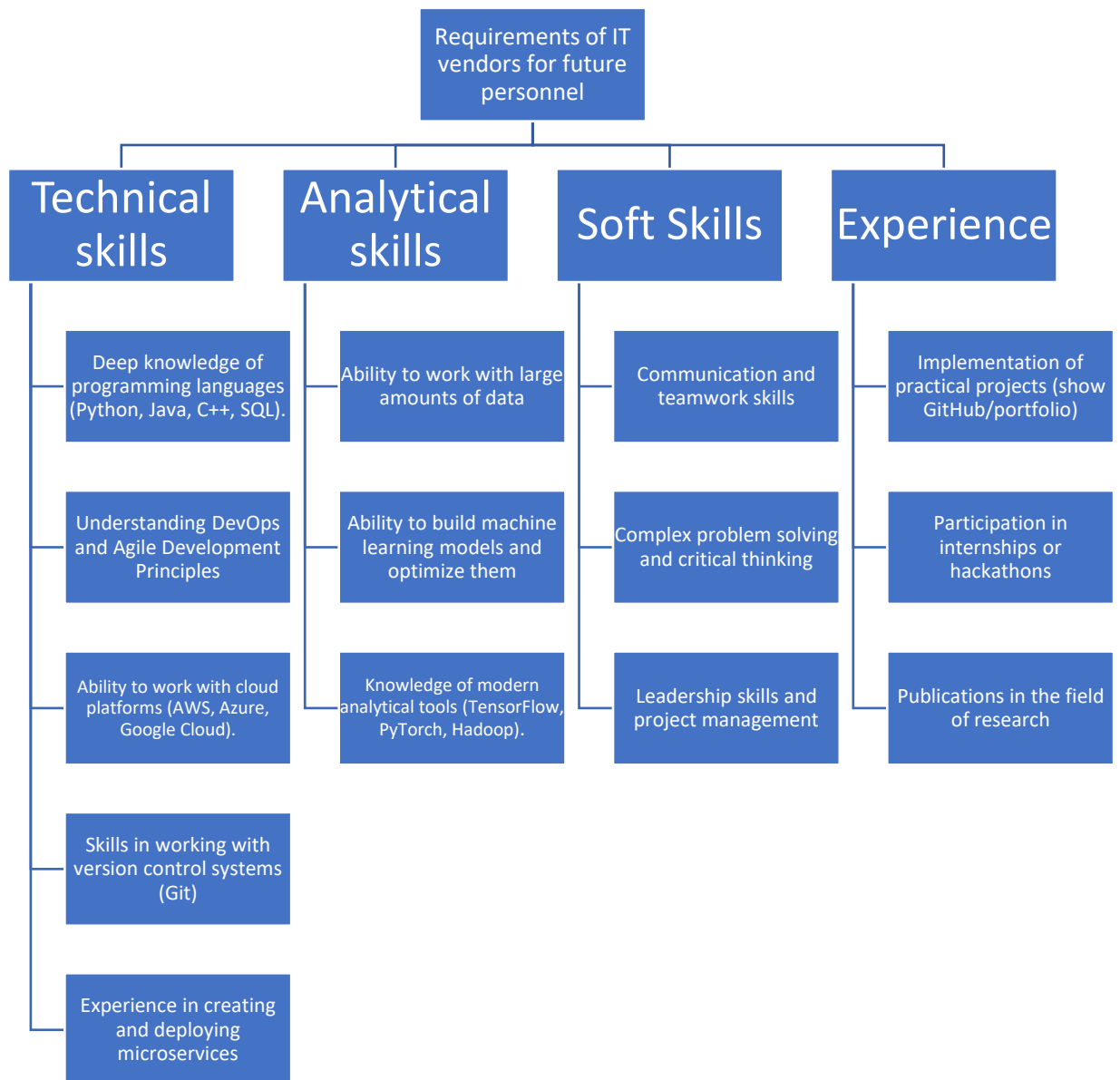


Figure 3.
Requirements of IT vendors for future personnel.

At the Massachusetts Institute of Technology (MIT), each IT program includes a unique set of disciplines to provide students with the necessary knowledge and skills for a successful career.

The requirements for candidates of such IT vendors as Microsoft, Cisco, Amazon, Google are described in Figure 4 [30].

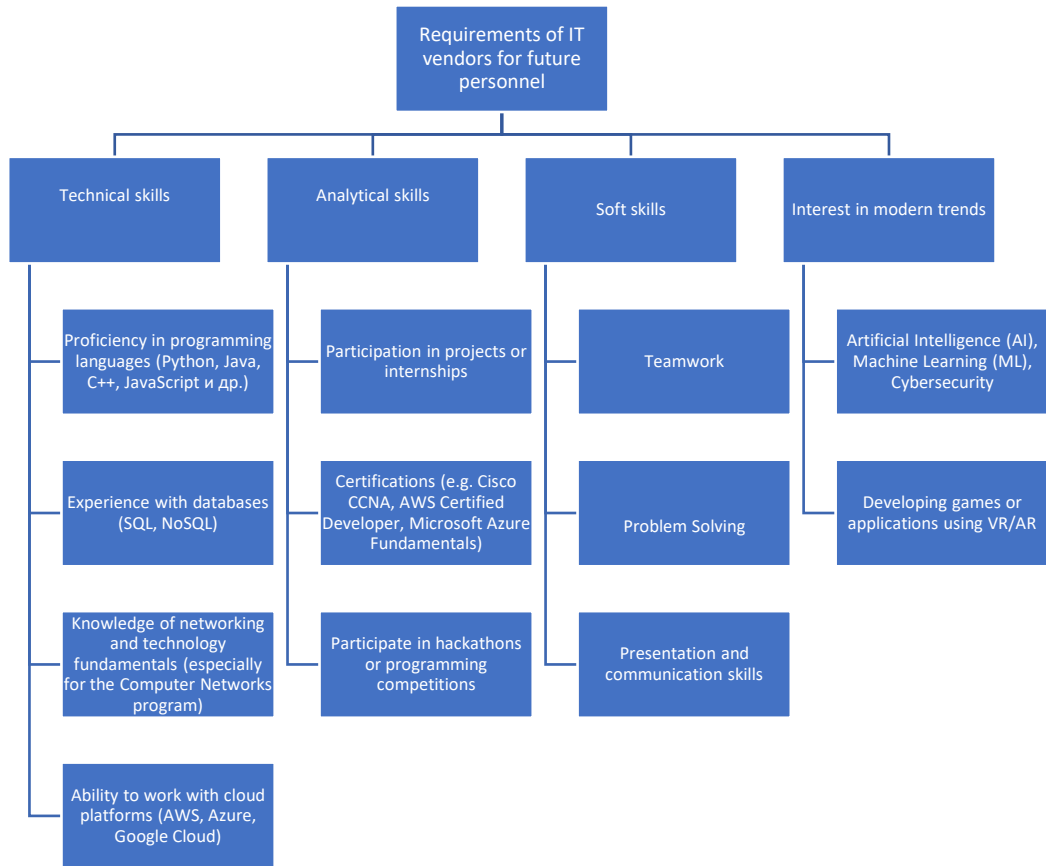


Figure 4. Requirements of IT vendors (Microsoft, Cisco, Amazon, Google).

The University of Leeds in the UK offers IT programs focused on various aspects of computer technology, from artificial intelligence to game engineering. To help students become competitive in the labor market, it is important to develop a wide range of competencies. Figure 5 considers the key requirements for the competencies of future IT personnel.

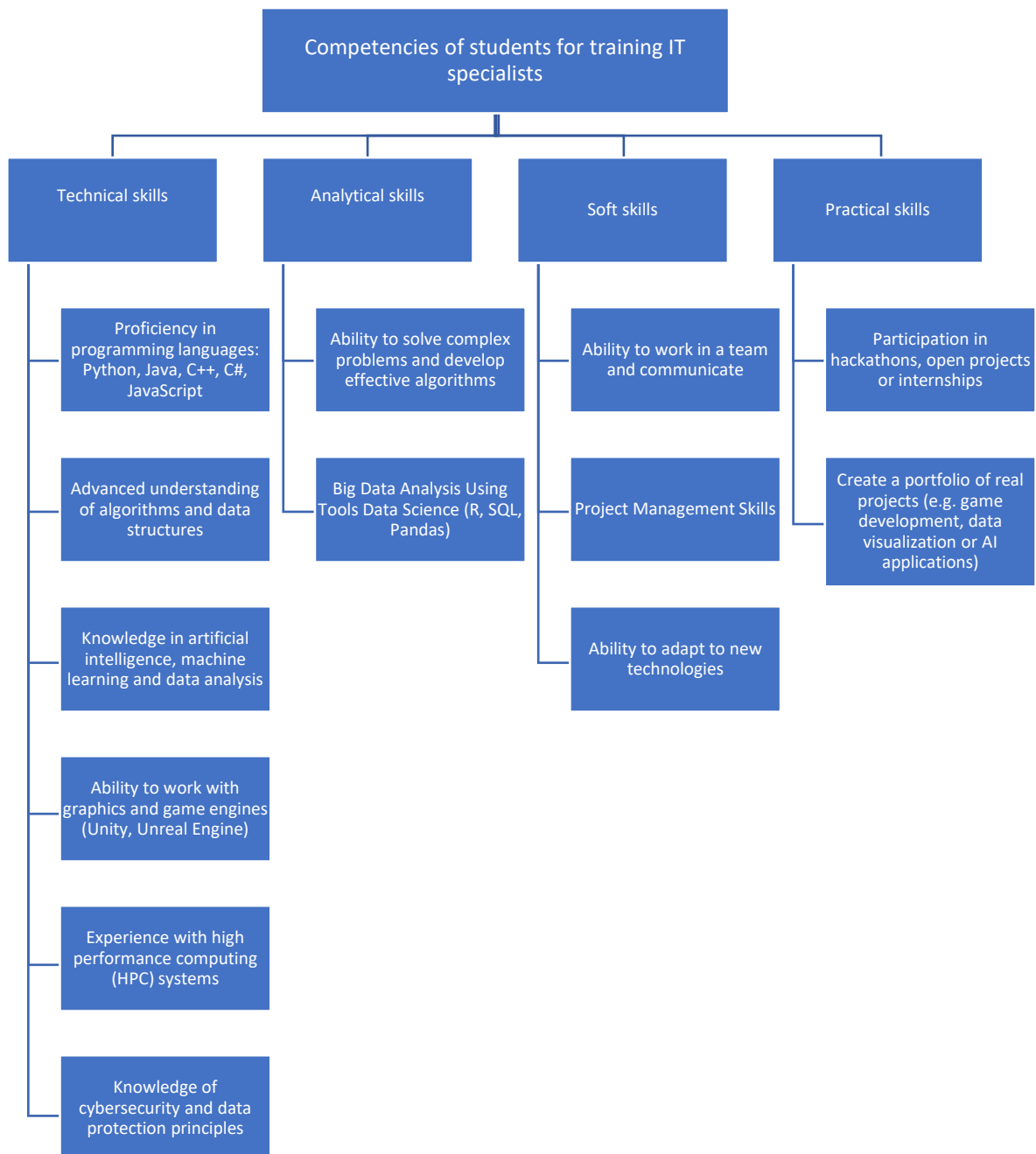


Figure 5. Students' competencies for the training of IT specialists.

Based on the analysis of the competencies imposed by universities on graduates and the requirements imposed by employers, it follows that the key parameters are: work experience, knowledge of theoretical material, analytical thinking, and communication (soft skills) (Figure 1-4).

In order to determine the likelihood of career growth based on the available data, let's consider the specialties "Information Systems" and "Computer Science" in the context of data on graduates, including:

- X₁: GPA;
- X₂: difficulty of disciplines;
- X₃: career benchmarks;
- X₄: participation in hackathons, internships and projects;
- Y: the probability of career growth (0 – did not get a job, 1 – got a job).

Next, we build a logistic regression model to predict the probability of career advancement based on these factors using correlation-regression analysis. Logistic regression can be used to analyze the relationship between the explanatory variables and the dependent variable (career probability) because the dependent variable Y has two values (0 or 1).

Logistic regression is used when the dependent variable is binary. A logistic regression model for predicting Y based on variables X₁, X₂, X₃, X₄ is described by the following formula:

$$P(Y = 1|X_1, X_2, X_3, X_4) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4)}}$$

Where is $P(Y = 1)$ – the probability of career growth (got a job),
 β_0 – free term (intercept),
 $\beta_1, \beta_2, \beta_3, \beta_4$ – Coefficients for Variables X_1, X_2, X_3, X_4 respectively.

Initially, set the coefficients as zero: $\beta_0=0, \beta_1=0, \beta_2=0, \beta_3=0, \beta_4=0$. These initial values can be changed during the optimization process.

First, let's calculate the linear combination. The linear combination (or logit function) for each observation is calculated using the formula:

$$\text{Linear combination} = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4$$

In Excel, for the first observation, for example, the formula would look like this:

$$\text{Linear combination} = 0 + 0 \times 3 + 0 \times 4 + 0 \times 1 + 0 \times 5 = 0$$

We repeat this for all observations. Next, calculate the probability forecast.

Now we need to calculate the probability that $Y=1$ using the logistic function:

$$P(Y = 1) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4)}}$$

In Excel, for the first row, the formula for probability would be:

$$P(Y = 1) = \frac{1}{1 + \exp(0)} = 0.5$$

Doing these calculations for all observations. Then we calculate the logarithm of the likelihood.

The logarithm of the likelihood for each observation is calculated using the formula:

$$\log \text{likelihood} = Y_i \cdot \log(P(Y_i = 1)) + (1 - Y_i) \cdot \log(1 - P(Y_i = 1))$$

For the first observation ($Y = 1$), it would be:

$$\log \text{likelihood} = 1 \cdot \log(0.5) + (1 - 1) \cdot \log(1 - 0.5) = \log(0.5)$$

Once you have calculated the plausibility logarithms for each observation, you need to add them up. To optimize the odds ($\beta_0, \beta_1, \beta_2, \beta_3, \beta_4$), you need to recalculate the logarithm of the likelihood to maximize it. To do this, you can use gradient descent or simply try different values of the coefficients and observe how they affect the value of the logarithm of the likelihood.

Excel was used for the calculations. Now, let's interpret the coefficients of the logistic regression model. Each coefficient in the logistic regression model reflects the influence of the corresponding attribute (variable) on the probability that the event will occur (in your case, that the graduate will find a job and be in demand, $Y = 1$).

General Model:

$$\log \text{it} (P(Y = 1)) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 X_4 ,$$

Where is $\log \text{it}(P(Y = 1))$ – This is the logit (logarithm of the probability ratio), which is converted to probability using a logistic function.

$X_1, X_2, X_3, \text{ и } X_4$ – These are the values of your traits (for example, the average score, complexity of disciplines, participation in projects, career guidelines).

Each change in odds affects the probabilities.

According to calculations

$$P(Y = 1) = \frac{1}{1 + \exp(-0.83)} \approx 0.696$$

This means that the probability of career advancement for this observation is approximately 69.6%.

If the coefficient at X_4 (participation in hackathons, internships, and projects) is the most significant, it indicates that participation in hackathons, internships, and projects is crucial for career growth, and the trajectory should be designed to include more practical experience.

Table 5.
Interpretation of each coefficient.

| No. | Factors | Interpretation |
|-----|-------------------|--|
| 1 | $\beta_0 = 0.23$ | This is the free term of the model (or intercept). It shows the logit (logarithm of the probability ratio) when all other variables (X_1, X_2, X_3, X_4) are zero. That is, when all signs are zero, the probability of career growth (getting a job) will be associated with this value. |
| 2 | $\beta_1 = 0.45$ | This coefficient refers to the variable X_1 (GPA). It shows how a 1-unit change in GPA affects the logit (logarithm of the probability ratio) that a person will get a job. If $\beta_1 > 0$, this means that an increase in GPA increases the likelihood of career advancement. An increase in the average score by 1 unit increases the logit by 0.45, which in turn increases the likelihood that a person will get a job. For example, if the average score increases from 3 to 4, then this will have a positive effect on the chances of success. |
| 3 | $\beta_2 = -0.12$ | This coefficient refers to the variable X_2 (difficulty of disciplines). It shows how a change in the complexity of disciplines by 1 unit affects the likelihood of career growth. Since β_2 is negative, this indicates that increasing the difficulty of the disciplines by 1 unit decreases the likelihood of obtaining a job. Interpretation – The higher the complexity of the disciplines, the lower the likelihood of career advancement. For example, if the complexity of disciplines increases, the likelihood that a person will get a job decreases slightly. |
| 4 | $\beta_3 = 0.08$ | This coefficient refers to the variable X_3 (participation in projects). It shows how a change in project participation by 1 unit affects the career probability log. A positive coefficient indicates that participation in projects increases the likelihood of getting a job. An increase in participation in projects (for example, participation in hackathons or internships) by one unit increases the probability of career growth by 0.08. |
| 5 | $\beta_4 = -0.07$ | This coefficient refers to the variable X_4 (career benchmarks). Since the coefficient is negative, this indicates that if a person has high career benchmarks, then the likelihood that he will get a job may decrease. Increasing the values of career benchmarks by 1 unit reduces the likelihood of career growth (getting a job). This may be due to the fact that a person with high career benchmarks may be more demanding and choose more prestigious vacancies, which can reduce the chances of employment. |

The second method of principal component analysis (PCA) – Principal Component Analysis – is suitable if we have many variables that can be interrelated (for example, different skills of students), and we want to identify the most significant factors that affect career growth.

Let's consider the study of the most significant factors affecting career growth using the principal component analysis (PCA). We have data on 115 students, including over 10 parameters such as Python, C++, algorithms, SQL, soft skills, etc. Instead of analyzing all these parameters individually, they were reduced to 2-3 principal components, which explain 80-90% of the variation in the data.

If the first major component (PC1) consists of 70% knowledge of algorithms and Python skills, and the second (PC2) consists of 60% soft skills and teamwork experience, then these two factors are key to successful career growth.

In the era of active development of artificial intelligence and its integration into the educational process, there are corresponding changes in the requirements for graduates' competencies. Our research highlights modern approaches to competency formation, including the Atlas of Emerging Professions, an analysis of digital opportunities in higher education, and the concept of HolonIQ, which provides an overview of key trends in education. These sources enable the identification of current changes and predicted trajectories within the IT environment. With the advancement of artificial intelligence (AI), new specialties have emerged in the field of information technology, such as those listed in the Atlas of New Professions and Competencies of Kazakhstan. One such specialty is the developer of universal AI, scheduled for 2025, focusing on developing algorithms and rules for analysis, decision-making, work, learning, self-learning, communication, interaction, and the development of universal AI. The novelty of this profession lies in enhancing AI and evolving it into an autonomous, self-learning entity. Key competencies for this profession include designing and developing universal self-learning AI, establishing principles and standards for its operation, and customizing universal AI for specific primary tasks.

A blockchain technologist is scheduled for 2025; this is a narrow-profile blockchain specialist who ensures the integration of blockchain technology into business processes. They organize intra-system and external interactions within the blockchain network, predict hashrate and complexity of calculations, monitor energy needs, and coordinate tasks for the network. The novelty of the profession popularizes blockchain platforms and expands the possibilities of their application in various fields.

The key competencies of the profession will be the development and implementation of blockchain networks; building architectures and organizing the interaction of many blocks; and the improvement and expansion of PACs in blockchain networks.

The Cyber Protector of Universal AI, scheduled for 2030, is a highly specialized professional engaged in developing and maintaining algorithms and systems to protect AI from external interference, cyber threats aimed at hacking, deceiving, or misleading AI to influence its decision-making process. The specialist assists AI in determining the direction, method, and content of cyberattacks, interpreting them correctly, and abstracting them. The novelty of this profession lies in the increasing complexity and potential of AI, as well as the growing importance of its decisions amid rising cyber threats, which will necessitate the training of individual specialists involved in AI protection. The key competencies of the profession include developing systems to protect AI from external influences to enable reconfiguration; collaborating with AI to objectify and adequately assess external interactions; and consulting AI in the field of self-defense.

An artificial neural network designer who designs models and architects artificial neural networks for specific domains. The novelty of the profession is that it will be necessary to solve the problems of expanding neural networks as the basis for the operation of universal AI, which causes the need for specialists who are able to design ultra-complex systems in the field of AI development and improvement. The key competencies of the profession are interaction with the primary recipient in terms of determining configuration requirements, the range of potential tasks, and algorithms for solving them; design of neural networks, their basic customization, and configuration [31].

Also, analyzing the article "Overview of trends in education in 2025: artificial intelligence, skills, and ways of developing the workforce," it is shown that artificial intelligence is becoming an integral part of education, just as interactive tools were once introduced into the teaching of disciplines. The main focus is also on the development of practical skills and the accelerated employment of graduates. Investors and governments support models for integrating education and the labor market. The most important roles are played by analytics, personalization of learning, and EdTech solutions, and flexible and alternative educational models are becoming the norm [32].

This analysis shows that education is currently being transformed towards practicality, flexibility, and digitalization, adapting to changes in the labor market and society.

7. Conclusion

Studies have shown that

1. Correlation analysis: A correlation matrix has been constructed, illustrating the relationships between various indicators. The analysis reveals the connection between the average score, the complexity of disciplines, and career benchmarks. The correlation suggests that academic success is associated with participation in startups, hackathons, and career guidance tests.

2. Principal Component Method (PCA): The first principal component explains 17.6% of the variance, and the second explains 8.2%. With only two components explaining 25.8% of the total variability, this indicates that students' career development is multifactorial.

3. Linear regression: coefficient of determination (R^2) = 0.43, which indicates that 43% of the variation in career growth is explained by educational factors. This confirms the influence of academic performance and student activities on their subsequent employment.

As a result, we conclude that students who actively participate in additional courses, internships, and projects show higher academic performance; however, teaching methods and the quality of materials significantly affect the level of mastery of disciplines. The PCA indicated that career development can be described by two main factors, but a more in-depth analysis is necessary for more accurate career forecasting: clustering students by types of career trajectories and studying the impact of soft skills on academic and career success.

The prospects for the study and development of data mining for the career growth of IT personnel are demonstrated by the fact that the field of computer science exhibits unavoidable novelty and high dynamism in the development of the IT industry, which makes the relevance of training competitive and in-demand IT personnel and the readiness of universities to quickly adapt their training systems.

References

- [1] J. E. Rafiq, Z. Abdelali, M. Amraoui, S. Nouh, and A. Bennane, "Predicting academic performance: Toward a model based on machine learning and learner's intelligences," *International Journal of Power Electronics*, vol. 15, no. 1, p. 9, 2025. <https://doi.org/10.11591/ijece.v15i1.pp645-653>
- [2] M. Liang, G. Zhou, W. He, H. Chen, and J. Qian, "A student performance prediction model based on hierarchical belief rule base with interpretability," *Mathematics*, vol. 12, no. 14, p. 2296, 2024. <https://doi.org/10.3390/math12142296>
- [3] K. Mahboob, R. Asif, and N. G. Haider, "Career planning matters: Intelligence-based career path predictions using data mining models - A longitudinal study," *Mehran University Research Journal of Engineering and Technology*, vol. 43, no. 4, pp. 192-213, 2024. <https://doi.org/10.22581/muet1982.3343>
- [4] S. O. Folorunso, Y. Farhaoui, I. P. Adigun, A. L. Imoize, and J. B. Awotunde, *Prediction of student's academic performance using learning analytics. In Y. Farhaoui, A. Hussain, T. Saba, H. Taherdoost, & A. Verma (Eds.), Artificial Intelligence, Data Science and Applications. ICAISE 2023 (Lecture Notes in Networks and Systems)*. Cham: Springer, 2024.
- [5] J. Zhang, G. Chen, Q. Yu, Y. Meng, Z. Lv, and J. He, "Longitudinal relations between future time perspective and academic engagement among chinese college students: The mediating role of career adaptability," *Current Psychology*, vol. 43, no. 48, pp. 37123-37137, 2024. <https://doi.org/10.1007/s12144-024-06951-0>
- [6] I. M. Ogundele, O. Taiwo, A. E. Babalola, and O. C. Ayeni, "Prediction of student academic performance based on machine learning model," presented at the IEEE Conference on Science, Engineering and Business for Sustainable Development Goals (SEB-SDG), 2024.
- [7] V. Loncarevic, V. Lekic, and N. Damljanović, "Predicting student academic success with hidden Markov models," presented at the 10th International Scientific Conference Technics, Informatics and Education – TIE 2024, 2024.

- [8] C. S. Bhoomika, S. Athreya, and V. Kanchana, "Data-driven Exploration of Personality and Cognitive Factors in Academic Performance Prediction," in *2024 Second International Conference on Networks, Multimedia and Information Technology (NMITCON)*, 2024, pp. 1-8.
- [9] S. Gupta and R. V. Varade, "A data-driven model for predicting the academic performance of students employing ANN-PSO hybrid approach," presented at the Network, Multimedia and Information Technology (NMITCON) International Conference, 2024.
- [10] R. Thamilselvan, R. R. Rajalaxmi, E. Gothai, M. K. Tabitha, M. Kirutheeswaran, and M. Logeshwaran, "Forecasting students academic achievement using machine learning techniques," in *2024 2nd International Conference on Artificial Intelligence and Machine Learning Applications Theme: Healthcare and Internet of Things (AIMLA)*, 2024, pp. 1-6.
- [11] V. N. Wijayaningrum, A. P. Kirana, and I. K. Putri, "Student academic performance prediction framework with feature selection and imbalanced data handling," *Jurnal Ilmiah Kursor*, vol. 12, no. 3, pp. 123-134, 2024. <https://doi.org/10.21107/kursor.v12i3.356>
- [12] K. C. Novo, "Predicting students' academic performance using data mining method," *International Journal of Latest Technology in Engineering Management & Applied Science*, vol. 13, no. 10, pp. 127-131, 2024. <https://doi.org/10.51583/IJLTEMAS.2024.131016>
- [13] A. P. A. Siregar, N. D. Qoyyimah, A. Surayya, S. Y. N. Nasution, and D. Y. Siregar, "The influence of educational internships on the development of student competencies," *Guruku: Jurnal Pendidikan Dan Sosial Humaniora*, vol. 2, no. 1, pp. 81-89, 2024.
- [14] R. A. Ferraz, "Internship in higher education: Transversal, socio-emotional and career skills," 2024. <https://doi.org/10.11606/d.59.2022.tde-06062024-133658>
- [15] N. N. Savelieva, "Professional training through participation in competitive activities," *11th International Scientific & Practical Conference "Culture, Science, Education: Problems and Perspectives"*; pp. 253-258, 2024.
- [16] J. M. Pardo Regueiro, M. de Los Angeles Constantino-González, O. O. López, M. Ángel López Mariño, A. S. Heredia, and F. Rubio Názer, "Competences development and significative learning through engineering design competition," in *2023 World Engineering Education Forum - Global Engineering Deans Council (WEEF-GEDC)*, 2023, pp. 1-6.
- [17] K. B. Alipina and A. A. Kitapbayeva, "Formation of research competencies of students," *Iasau Universitetinin Habarshysy*, vol. 4, no. 30, pp. 344-360, 2023. <https://doi.org/10.47526/2023-4/2664-0686.28>
- [18] Y. S. Balcioğlu and M. Artar, *Predicting academic performance of students with machine learning. Information Development*. Thousand Oaks, CA, USA: SAGE Publications, 2023.
- [19] G. B. Iwasokun, F. O. Sunmola, and F. O. Sunmola, "Forecasting student academic performance using neuro-fuzzy model," *European Journal of Applied Sciences*, vol. 11, no. 3, pp. 243-268, 2023. <https://doi.org/10.14738/aivp.113.14773>
- [20] I. F. D. Sousa *et al.*, "The role of internship practices in initial teacher training," 2024. <https://doi.org/10.69849/revistaft/ar10202410170818>
- [21] Y. Rachma, A. Sutarman, D. H. Andayani, H. Haryani, and S. Johnson, "Analysis of HR career development strategies in the era of artificial intelligence," in *Proceedings of the IEEE International Conference on Communications, Internet, and Technology (IC-CIT)*, pp. 1-7. New York, NY, USA, 2024.
- [22] D. Badulescu, R. Simut, S.-A. Bodog, A. Badulescu, C. Simut, and D. Zapodeanu, "Shaping AI-related competencies for labor market and business. A PLS-SEM approach," *International Journal of Computers Communications & Control*, vol. 20, no. 1, pp. 105-120, 2025.
- [23] Y. Miao and Y. Yao, *Professional development of college teachers in the era of artificial intelligence: Role rebuilding and development path*. Cham: Springer, 2020.
- [24] S. Chatterjee, "Evaluating the effects of AI-powered training programs on skill development and career growth," *International Journal of Advanced Research in Science, Communication and Technology*, vol. 1, no. 1, pp. 941-945, 2023.
- [25] A. Kumar, R. Kumar, and P. Raghuvanshi, "Navigating industry 4.0: Exploring the impact of AI on employment & jobs in India," *Indian Scientific Journal of Research in Engineering and Management*, vol. 8, no. 11, pp. 1-5, 2024.
- [26] A. Chauhan, S. Sachan, A. Arya, A. Kumar, and S. Tripathi, "Reeducating for the artificial intelligence (AI) century," *International Journal of Innovative Science and Research Technology*, vol. 9, no. 9, pp. 641-646, 2024. <https://doi.org/10.38124/ijisrt/IJISRT24SEP680>
- [27] S. Jing, X. Liu, X. Gong, and H. Zhao, "System dynamics-based analysis on factors influencing artificial intelligence talents training," *IEEE Journal of Radio Frequency Identification*, vol. 6, pp. 753-757, 2022. <https://doi.org/10.1109/JRFID.2022.3216063>
- [28] G. Călinescu and M. Tanaşciuc, "Redefining the skills required on the labour market in the context of the development of artificial intelligence systems. Case study on finnish universities," *Romanian Economic Journal*, vol. 27, no. 88, pp. 63-74, 2024.
- [29] Z. Ullah, E. J. Solteiro Pires, A. Reis, R. R. Nunes, A. A. Khan, and J. Barroso, "Artificial intelligence transformative power in the fourth industrial revolution: A systematic review of process and workforce impact," *SSRN*, 2025. <https://doi.org/10.2139/ssrn.5079230>
- [30] Cisco, "Apple и Microsoft: Current internships in IT companies around the world," 2025. <https://the-tech.kz/cisco-apple-i-microsoft-aktualnye-stazhirovki-v-it-kompaniyah-mira/>
- [31] Ministry of Labor and Social Protection of the Republic of Kazakhstan, "Atlas of new professions and competencies of Kazakhstan," 2025. <https://atlasbt.enbek.kz/ru/professions?department=4&trends=&skills=9>. [Accessed July 12, 2025]
- [32] HolonIQ, "Education trends in review 2025: Artificial intelligence, skills, and workforce development pathways. HolonIQ," 2025. <https://www.holoniq.com>