

N. Kuzembayeva* , Sh. Nurgazy ,
A. Kaliyeva , D. Khalizhan 

Al-Farabi Kazakh National University, Almaty, Kazakhstan

*e-mail: kanurarii@mail.ru

THE IMPACT OF ARTIFICIAL INTELLIGENCE ON ORGANIZATIONAL PERFORMANCE

Received: February 18, 2025

1st Revision: March 3, 2025

Accepted: March 15, 2025

Abstract. This research explores how faculty training and development initiatives influence organizational performance within Kazakhstan's higher education institutions. It further examines the mediating effect of AI adoption on this relationship.

A structured questionnaire was used as the primary method for data collection, with responses gathered from a sample of 218 employees working in higher education institutions across Kazakhstan.

The results indicate that AI adoption serves as an intermediary factor between training and development practices and organizational performance, confirming the proposed research model.

Additionally, the study introduces a theoretical framework based on Career Construction Theory to analyze AI adoption's potential role in shaping organizational performance. By integrating both institutional and individual factors, this research provides deeper insights into the drivers of organizational performance.

Key words: training and development; AI adoption; organizational performance; Higher Education; Quantitative.

Introduction

The last decade has been a time of rapid development of artificial intelligence, especially in terms of its application in various fields. Bresnahan (2016) stated that the application of AI requires a complete restructuring of the organization, after which it can be considered as an information technology. This statement was based on a large amount of research and the fundamentals of AI implementation in this area. Mehr et al. (2017) noted some of the most important applications of artificial intelligence, such as process automation, knowledge management, fraud detection, etc. In this article, we are going to discuss the use of artificial intelligence, especially in universities, as well as consider training programs for the implementation of artificial intelligence. The introduction of AI is crucial not only for individual businesses, but also for the economy as a whole, as the pandemic has shown that AI expands interactive opportunities and accelerates processes (Madsen & Strulik, 2023). The use of artificial intelligence has helped companies more than initially expected. Various empirical studies confirm this statement. Ac-

cording to McKinsey (2019), the adoption of AI is growing, and companies implementing AI in various departments are seeing huge revenue growth along with cost reductions. As companies compete for leadership in the digital world, AI adoption has become a critical area for efficiency, innovation, and strategic decisions (Duan et al., 2019; Dwivedi et al., 2021; Knight, 2015). However, its implementation also requires structural changes, staff development, and ethical standards to fully realize its potential. It is important to understand the contribution of AI to organizational effectiveness in order to develop strategies to harness its potential and overcome its challenges. Recently, a growing body of research has focused on AI implementation across various sectors, including healthcare, manufacturing, smart homes, banking, programming, and more (Mehr et al., 2023). However, due to its vast scope, many questions remain open for future researchers. For instance, existing literature does not sufficiently cover AI implementation in higher education institutions or justify the necessity of studying AI in this educational context.

Previous research has not given enough significance to the variety of learning settings or the use

of AI in the learning process for students and educators. It can be argued that a significant gap in research is the lack of focus on AI integration in universities, despite its growing relevance in this field. Savickas (2005) proposed the “career construction theory” concept, which suggests that individual career development is a process of adaptation between a person and a dynamic external world. Compared to other career theories, career construction theory helps students adapt to the complex and evolving job market of the future and encourages a broader perspective on career development (Gao & Qiao, 2022).

Understanding how artificial intelligence is integrated into the academic environment can enhance students’ preparedness to work with AI in companies in the future and improve learning outcomes.

For this study, we will conduct a survey among university faculty members to examine how training and development influences AI implementation, and its impact on organizational efficiency. The objective of this research is to analyze AI adoption in higher education institutions and develop effective recommendations for its integration into the educational system.

Literature review

The potential success of an organization depends on its performance, which reflects its ability to effectively implement strategies and achieve institutional objectives (Randeree and Al Youha, 2009). An organization’s performance is not only determined by its strategic implementation but also by its employees, who play a crucial role in driving its success. As the core of the organization, they collaborate to achieve institutional objectives, making their skills and adaptability essential for overall effectiveness (Mukherjee et al., 2012). To enhance organizational performance, institutions must continuously adapt to technological advancements that optimize efficiency and decision-making. One such transformative technology is artificial intelligence, which has the potential to streamline operations, improve analytical capabilities, and support employees in performing complex tasks.

Many scholars have attempted to define the concept of artificial intelligence. AI is a field of science dedicated to creating intelligent systems and software capable of analyzing information, learning, making decisions, interacting with the environment, and performing complex tasks. The term “artificial intelligence” was introduced by John McCarthy in 1956 and refers to a branch of computer science aimed at

developing technologies that simulate human thinking and behavior.

There have also been studies on the adoption of AI in organizations, primarily based on the TOE and TAM theories (Chatterjee S. 2021). In our literature review, we examined and analyzed the aforementioned studies. Among the leading research topics on AI implementation in organizations are: autonomous vehicles, big data analytics, robotics, and more (Jayanthi Radhakrishnan, Manojit Chattopadhyay, 2020). We decided to contribute to this field by studying AI adoption in universities. Acemoglu and Restrepo (2018) emphasize that automation is transforming the labor market by replacing routine tasks and creating new jobs that require advanced skills. In this context, education plays a critical role in the AI adaptation process. Brynjolfsson, Rock, and Syverson (2018) argue that organizations investing in employee upskilling gain greater benefits from AI, as trained professionals adapt to new technologies more quickly and increase productivity.

T&D and AI adaption

The approach to employee training and development has evolved significantly over time. While the early twentieth century focused on mass upskilling in batches, modern training emphasizes personalized and individualized learning tailored to specific needs (Souvik Maity, 2019). In some cases, firms can minimize or even eliminate net training costs during apprenticeships. This effectively reduces the marginal cost of training future skilled workers to near zero, particularly for specialized tasks (Muehlemann and Wolter, 2020; Wolter and Ryan, 2011). As a result, in countries with strong apprenticeship systems, such as Germany, labor costs for workers with AI-related skills can be significantly lower when acquired through apprenticeship programs compared to continuous training or external hiring. Implementing structured training protocols not only helps firms familiarize themselves with new technologies but also enhances their digital innovation performance and productivity (Soetekouw & Angelopoulos, 2022). Addressing skill gaps through targeted training interventions is essential to preparing the workforce for AI-driven transformations. Research suggests that AI training should go beyond basic IT exposure and include advanced competencies such as machine learning, AI integration, and the ethical use of AI (Doi, 2023).

H1: Training and development positively affects to AI adoption

AI adoption and organizational effectiveness

Chatterjee et al. (2021) emphasize the transformative impact of AI on organizational processes, highlighting its role in enhancing efficiency and decision-making. One of AI's key advantages is its ability to rapidly analyze vast datasets, allowing institutions to optimize operations, allocate resources effectively, and improve overall performance. By leveraging AI-driven insights, universities can enhance administrative processes, streamline academic management, and support data-driven decision-making.

The adoption of business analytics further strengthens institutional performance by enabling accurate processing and analysis of data collected through various academic and operational activities (Akter et al., 2019a, b). Technological advancements have consistently been linked to improved organizational performance, with studies demonstrating that AI-driven tools contribute to higher efficiency and better strategic planning in various sectors, including education (Marchiori et al., 2022; Mariani et al., 2023; Parteka & Kordalska, 2023; Pillai & Srivastava, 2023).

Moreover, generative AI (GenAI) plays a crucial role in supporting institutional operations by providing stakeholders with real-time insights and automating routine tasks, thereby enhancing productivity and innovation (Chu, 2023; Wamba et al., 2023; Raj et al., 2023). Research on AI applications such as ChatGPT also supports its positive impact on organizational performance, reinforcing the growing importance of AI integration in higher education management (Chu, 2023; De Smet et al., 2023).

Similarly, in higher education, Selwyn (2019) highlights that preparing students to work in AI-driven environments enhances their competitiveness and adaptability in the job market. Moreover, AI contributes to overall organizational efficiency by accelerating data analysis and optimizing business processes (Davenport & Ronanki, 2018). Haefner et al. (2021) demonstrate that companies using AI in workforce management and business operations achieve higher productivity and greater employee satisfaction.

H2: AI adoption positively affects to Organizational Performance

Mediating role of AI between T&D and organizational performance

AI plays a vital role throughout the entire training life cycle, from assessing training needs to delivering customized learning experiences, enabling learners

to progress at their own pace while enhancing retention rates (Upadhyay & Khandelwal, 2019).

Despite the extensive research on this topic, several gaps remain, particularly in understanding the long-term effects of AI on the labor market and the role of universities in training specialists capable of effectively working with these technologies. Future research should address these aspects to provide a deeper understanding of the mechanisms behind AI integration across different industries.

According to the "Career Construction" theory, the adaptation model in career development suggests that individuals differ in their readiness and ability ("adaptation resources" or "career adaptability") to act in ways that align with changing environmental conditions. This raises the idea that AI adoption is perceived differently by individuals, but if they are properly prepared for these changes, it can lead to greater success. By providing adaptive learning environments, AI ensures that training programs are tailored to individual skill levels, enhancing knowledge acquisition and workforce readiness. This, in turn, facilitates a smoother transition of newly acquired skills into practical applications within the organization, ultimately leading to improved operational efficiency and performance. As AI optimizes training methodologies and knowledge transfer, it acts as a crucial mediator, bridging the gap between training and development (T&D) efforts and measurable improvements in organizational performance.

H3: AI adoption mediates the relationship between T&D and Organizational Performance

Methodology

A total of 350 questionnaires were distributed among faculty members in natural sciences, mathematics, economics, and technology at leading national universities in Astana and Almaty. These cities serve as Kazakhstan's main educational hubs. In total, we received 218 responses, of which 198 were used for analysis, while the remaining responses were excluded due to incomplete data or invalid answers. The actual response rate was 56%. Among the respondents, 60.7% were women, while 39.3% were men. The age distribution of the respondents was as follows: 5% were between 20-24 years old, 34.3% were between 25-29 years old, 18.2% were between 30-39 years old, 25.1% were between 40-49 years old, and 17.4% were over 50 years old. Their work experience ranged from one to twenty years.

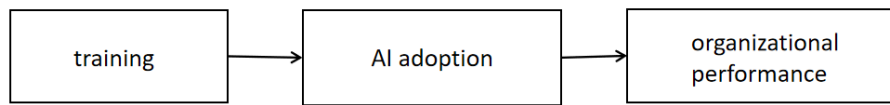


Figure 1 – Research Framework

Measures

The measurement for each construct was taken from previously validated sources. All constructs were assessed using a Likert scale ranging from “strongly disagree” to “strongly agree.”

T&D

Training aims to equip individuals with the knowledge, skills, and mindset required to carry out job-related tasks effectively, with the primary goal of directly enhancing job performance. (True-love, 1992: 273) The questions for **Training and Development** were adapted from Gertner & Nollen (1989) and consisted of five items. An example question is: “*Training is considered a way to improve productivity.*” The Cronbach’s alpha for this scale was 0.83.

AI adoption

AI adoption is the process of “integration of new and diverse knowledge through the creation...of new capabilities, technologies and training programmes” (Ashok et al., 2016, p. 1008). The **AI** construct was

adapted from Wang et al. (2016), with an example question: “*The management of our organization is likely to invest in AI technology implementation.*” The Cronbach’s alpha for this scale was 0.91.

Organizational performance

The final variable, **Organizational performance (OE)**, was taken from Deshpande et al. and Drew (1993) and consisted of five items. Organizational performance refers to an organization’s ability to efficiently accomplish its objectives and fulfill its strategic goal (Selden & Sowa, 2004), with each item beginning with the phrase: “*Compared to our main competitors...*” The Cronbach’s alpha for this scale was 0.89. An example item is: “*Compared to our main competitors, our organization is growing faster.*”

For data analysis, **SmartPLS 4.0** and the **PLS-SEM model** were used. The choice of this software was based on its widespread use and preference as a method for structural equation modeling. As a result, we got the following model:

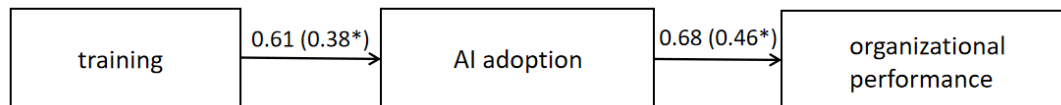


Figure 2 – Research Model

The mean values, Cronbach’s alpha, and standard deviation for each question were also calculated.

The Cronbach’s alpha values, as a measure of reliability, were all above the recommended threshold of 0.7. Additionally, the mean values were above 0.6.

Additionally, to analyze our research model, we employed the bootstrapping technique to test the hypotheses of mediated moderation, using 5,000 resampling bootstrap samples.

Results

Reliability and validity

To test the measurement model, we tested reliability, convergent validity, and discriminant validity. The reliability of each design was assessed us-

ing the Cronbach’s alpha coefficient, which ranged from 0.83 to 0.91, which exceeds the recommended threshold of 0.7 (Nunnally & Bernstein, 1967). For further reliability testing, composite reliability (CR) was also calculated, and all values ranged from 0.86 to 0.93, which exceeds the minimum threshold of 0.7. Convergent validity was verified using the method proposed by Fornell and Larker (1981), which requires that the mean extracted variance (AVE) be greater than 0.50. Our results confirm that all AVE have reached this threshold. To test discriminant validity, we used the Fornell and Larker criterion (1981), which requires that the square root of AVE exceed the correlations of the construct. Our results show that this criterion was met, which confirms the discriminant validity.

Table 1 – Latent variable correlation matrix, internal consistency and average variance extracted

	Ai adoption	Training	Organizational effectiveness	Composite reliability	Cronbach's coefficient	AVE	AVE (square root)
Ai adoption	-			0.94	0.91	0.85	0.9
Training	0.61***	-		0.88	0.83	0.66	0.8
Organizational effectiveness	0.68***	0.83**	-	0.92	0.89	0.71	0.9

Note: t-values > 1.65* (p < 0.1); t-values > 1.96** (p < 0.05); t-values > 2.57*** (p < 0.001)

Research results validated both suggested hypotheses, affirming that training is a determining variable in the AI implementation process and AI itself has a positive influence on organizational performance. In order to determine the statistical significance of the

variable relationships, p-values were utilized. As the p-values obtained were less than the standard cutoff value of 0.05, the findings show that the observed effects are statistically significant and thus validate the hypothesized hypotheses.

Table 2 – Testing mediation

Paths	Standardized coefficients (t-values)	
	Direct effects	Indirect effects
Ai adoption -> Organizational effectiveness	0.68 (10.8***)	
Training -> ai adoption	0.61 (6.8***)	
Training -> ai adoption -> Organizational effectiveness	0.42 (4.6***)	0.42 (4.6***)

Note: t-values > 1.65* (p < 0.1); t-values > 1.96** (p < 0.05); t-values > 2.57*** (p < 0.001)

To begin with, evidence showed that training was one of the main determinants of AI adoption success ($\beta = 10.803$, $p < 0.05$). That is, the more students and staff are trained on matters related to AI, the better and easier such technologies are adopted into organizational procedures. Well-trained users adapt more quickly to new tools, enhancing the overall digital maturity of the organization.

Second, the analysis revealed that **AI implementation has a significant positive impact on organizational performance** ($\beta = 6.88$, $p < 0.05$). Organizations that adopt AI optimize processes, accelerate data processing, and improve decision-making, ultimately leading to increased productivity and better overall performance.

Additional calculations confirmed the **reliability of the scales used**: Cronbach's alpha for all indica-

tors exceeded **0.7**, indicating a high level of internal consistency in the data.

Furthermore, significant positive **correlations** were identified between the key variables, supporting the logical relationships within the model. The **p-values** were all below **0.05**, confirming the statistical significance of the findings.

Discussion and Conclusion

Our empirical results confirm the role of learning in ensuring the successful implementation of artificial intelligence (AI) and its beneficial impact on organizational effectiveness. Our results showed that the acquisition of AI-related skills by employees makes it possible to successfully implement such technologies in organizational practice, which is consistent with the literature (Wamba S.F., 2022).

Based on the theory of career building (Savickas, 2005), the study provides an improved understanding of the process of the proposed model. The model serves to explain how training affects employees' adaptability to technological progress, i.e. AI, and how this affects organizational effectiveness in general. By integrating these theoretical observations, our research complements both academic science and practice, emphasizing the need for continuous professional development in the age of digitalization. Our research has established, firstly, that learning is at the heart of effective AI implementation. These results are consistent with the literature, which emphasizes that employees should be provided with the necessary skills and knowledge to successfully collaborate with AI technologies (Sidhu, G. S., et al, 2024). Moreover, continuous learning promotes flexibility, which ensures that employees can easily integrate AI into organizational processes. Secondly, we found that the introduction of AI significantly improves organizational productivity, which is consistent with what is observed in the literature. This means that organizations using AI are able to automate processes, achieve improved decision-making and greater overall efficiency. Therefore, we conclude that the introduction of AI mediates the link between learning and organizational effectiveness, allowing organizations to transform acquired opportunities into measurable productivity gains and sustainable competitive advantages.

Practical implications

This research emphasizes the practical advantages of AI incorporation in training and development for the purpose of improving organizational efficiency, particularly in universities. AI has the potential to render education processes more effective

through the automation of administrative processes, customization of learning, and improvement of data-based decision-making. AI also prepares the faculty and students with future job market skills in AI that render them more competitive. Besides, AI simplifies operations by automating routine processes so that staff can concentrate on more value-added tasks. Its scalability enables quality education for everyone, while its flexibility positions institutions to be future-proof and innovative. Through the strategic adoption of AI, organizations are able to enhance productivity, efficiency, as well as long-term success.

Limitations and future research

As this research had certain limitations, for example, the sample, the narrow focus of the research, and being only in the Kazakhstani context, future research needs to aim at more than a single school or move into other sectors like healthcare, schools, and other business organizations. Our study serves applied use by validating current theory and empirical findings. Additionally, confirming the mediating role of AI provides valuable insights into its influence on various individual theories and business practices. This study enhances the understanding of AI adoption and broadens opportunities for further research with additional variables.

However, it would be interesting to conduct future studies in different settings with an expanded scope. Moreover, since all survey questions were self-collected and adapted, there is a potential methodological bias. Additionally, the data was gathered from a single university in one city, which may introduce sampling bias. Therefore, future research should aim for a broader dataset to ensure more comprehensive and generalizable findings.

References

- Acemoglu, D., & Restrepo, P. (2018). Artificial intelligence, automation, and work. *SSRN Electronic Journal*. <https://doi.org/10.2139/ssrn.3098384>
- Akter, S., Wamba, S. F., & D'Ambra, J. (2019). Enabling a transformative service system by modeling quality dynamics. *International Journal of Production Economics*, 207, 210–226.
- Ashok, M., Narula, R., & Martinez-Noya, A. (2016). How do collaboration and investments in knowledge management affect process innovation in services? *Journal of Knowledge Management*, 20(5), 1004–1024. <https://doi.org/10.1108/jkm-11-2015-0429>
- Bresnahan, T., & Yin, P. (2016). Adoption of new information and communications technologies in the workplace today. *National Bureau of Economic Research*. <https://doi.org/10.3386/w22346>
- Chatterjee, S., Rana, N. P., Dwivedi, Y. K., & Baabdullah, A. M. (2021). Understanding AI adoption in manufacturing and production firms using an integrated TAM-TOE model. *Technological Forecasting and Social Change*, 170, 120880. <https://doi.org/10.1016/j.techfore.2021.120880>
- Chu, M. N. (2023). Assessing the benefits of ChatGPT for business: An empirical study on organizational performance. *IEEE Access*, 11, 76427–76436. <https://doi.org/10.1109/ACCESS.2023.3297447>
- De Smet, A., Durth, S., Hancock, B., Baldocchi, M., & Reich, A. (2023). *The human side of generative AI: Creating a path to productivity*. McKinsey & Company.
- Deshpandé, R., Farley, J. U., & Webster, F. E. (1993). Corporate culture, customer orientation, and innovativeness in Japanese firms: A quadrad analysis. *Journal of Marketing*, 57(1), 23–37. <https://doi.org/10.1177/002224299305700102>

- Duan, Y., Edwards, J. S., & Dwivedi, Y. K. (2019). Artificial intelligence for decision making in the era of big data: Evolution, challenges, and research agenda. *International Journal of Information Management*, 48, 63–71. <https://doi.org/10.1016/j.ijinfomgt.2019.01.021>
- Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., ... Williams, M. D. (2019). Artificial intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice, and policy. *International Journal of Information Management*, 57, 101994. <https://doi.org/10.1016/j.ijinfomgt.2019.08.002>
- Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, 18(1), 39–50. <https://doi.org/10.1177/002224378101800104>
- Gaertner, K. N., & Nollen, S. D. (1989). Career experiences, perceptions of employment practices, and psychological commitment to the organization. *Human Relations*, 42(11), 975–991. <https://doi.org/10.1177/001872678904201102>
- Gao, Y., & Qiao, Z. (2022). From matching to construction: Transformation and realization of high school career education theory under the background of the new college entrance examination. *Employment of Chinese University Students*, 6, 3–10. <https://doi.org/10.20017/j.cnki.1009-0576.2022.06.001>
- Haefner, N., Wincent, J., Parida, V., & Gassmann, O. (2020). Artificial intelligence and innovation management: A review, framework, and research agenda. *Technological Forecasting and Social Change*, 162, 120392. <https://doi.org/10.1016/j.techfore.2020.120392>
- Mehr, H., Ash, H., & Fellow, D. (2017). *Artificial intelligence for citizen services and government*. Harvard Kennedy School.
- Knight, B. A. (2015). Teachers' use of textbooks in the digital age. *Cogent Education*, 2(1), 1015812. <https://doi.org/10.1080/2331186x.2015.1015812>
- Madsen, J., & Strulik, H. (2023). Testing unified growth theory: Technological progress and the child quantity–quality tradeoff. *Quantitative Economics*, 14(1), 235–275. <https://doi.org/10.3982/qe1751>
- Mukherjee, D., Lahiri, S., Mukherjee, D., & Billing, T. K. (2012). Leading virtual teams: How do social, cognitive, and behavioral capabilities matter? *Management Decision*, 50(2), 273–290.
- Nunnally, J. C., & Bernstein, I. H. (1967). *Psychometric theory* (1st ed.). McGraw-Hill.
- Savickas, M. L. (2005). The theory and practice of career construction. In S. D. Brown & R. W. Lent (Eds.), *Career development and counseling: Putting theory and research to work* (pp. 42–70). Wiley.
- Truelove, S. (1992). *Handbook of training and development*. Blackwell.
- Upadhyay, A. K., & Khandelwal, K. (2019). Artificial intelligence-based training: Learning from application. *Development and Learning in Organizations: An International Journal*, 33(2), 20–23. <https://doi.org/10.1108/DLO-05-2018-0058>
- Wamba, S. F. (2022). Impact of artificial intelligence assimilation on firm performance: The mediating effects of organizational agility and customer agility. *International Journal of Information Management*, 67, 102544. <https://doi.org/10.1016/j.ijinfomgt.2022.102544>
- Wang, Y., Li, H., Li, C., & Zhang, D. (2015). Factors affecting hotels' adoption of mobile reservation systems: A technology–organization–environment framework. *Tourism Management*, 53, 163–172. <https://doi.org/10.1016/j.tourman.2015.09.021>

Information about authors:

- Kuzembayeva Nurailym (corresponding author) – student 4th course of the Department of economics, Al-Farabi Kazakh National University (Almaty, Kazakhstan, e-mail: kanurail@mail.ru)
- Nurgazy Shynggys – PhD candidate, senior lecturer of the Department of economics, Al-Farabi Kazakh National University (Almaty, Kazakhstan, e-mail: shynggys.nurgazy@kaznu.edu.kz)
- Kaliyeva Assem – PhD, senior lecturer of the Department of economics, Al-Farabi Kazakh National University (Almaty, Kazakhstan, e-mail: assem.kaliyeva@kaznu.edu.kz)
- Khalizhan Diana – student 3rd course of the Department of economics, Al-Farabi Kazakh National University (Almaty, Kazakhstan, e-mail: halizhan.diana@jmail.com)