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Araştırma Makalesi

EFFICIENCY MEASUREMENT OF ARTIFICIAL INTELLIGENCE: A RESEARCH ON COMPANIES IN TÜRKİYE

(YAPAY ZEKÂ ETKİNLİK ÖLÇÜMÜ: TÜRKİYE'DE ŞİRKETLER ÜZERİNE BİR ARAŞTIRMA)

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ABSTRACT

The use of technology is increasing due to Industry 4.0. Both countries and organizations have had to invest in the field of artificial intelligence (AI) to compete with their rivals in global competitive conditions and to adapt to the ever-changing world. An organization or a country needs to evaluate its performance to ensure its sustainability constantly. The Data Envelopment Analysis (DEA) method is widely used in performance evaluation. This study aimed to evaluate Türkiye AI performance for the nine years between 2014 and 2022. In the research, years were included in the analysis as the decision-making unit. Two input and two output variables were used in the analyses. The study was carried out by using the input-oriented CCR DEA model and its super-efficiency model. According to the results of the analysis, efficient/inefficient decision-making units were determined. Several potential improvement suggestions have been put forward for inefficient decision-making units.

Keywords: Industry 4.0, Performance, Efficiency, DEA, Artificial Intelligence

JEL Classification: L25

ÖZ

Endüstri 4.0'a bağlı olarak teknoloji kullanımı her geçen gün artmaktadır. Gerek ülkeler gerekse organizasyonlar küresel rekabet koşullarında rakipleriyle mücadele edebilmek ve sürekli değişen dünyaya uyum sağlayabilmek için yapay zekâ alanına yatırımlar yapmak zorunda kalmıştır. Bir organizasyonun veya ülkenin sürdürülebilirliğini sağlayabilmesi için performansını değerlendirmesi oldukça önemlidir. Veri Zarflama Analizi (VZA) yöntemi performans değerlendirmesinde yaygın bir şekilde kullanılmaktadır. Bu çalışmada Türkiye'nin 2014-2022 yılları arasındaki dokuz yıl için yapay zekâ performansının değerlendirmesi amaçlanmıştır. Araştırmada, karar verme birimi olarak yıllar analize dâhil edilmiştir. Analizlerde iki girdi ve iki çıktı değişkeni kullanılmıştır. Çalışma girdi odaklı CCR VZA ve süper etkinlik modeli kullanılarak gerçekleştirilmiştir. Analiz sonuçlarına göre etkin olan/olmayan karar verme birimleri belirlenmiştir. Etkin olmayan karar verme birimleri için potansiyel iyileştirme önerileri sunulmuştur.

Anahtar Kelimeler: *Endüstri 4.0, Performans, Etkinlik, VZA, Yapay Zekâ*

JEL Kodları: *L25*

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1. INTRODUCTION

As a result of technological developments, change and transformation continue rapidly. Especially today, with artificial intelligence (AI), algorithms that bring the characteristic features of human intelligence to computers and systems that can produce solutions to problems by exhibiting human-like intelligent behavior are being developed (Öztemel, 2020). AI, which combines computer science and data sets, is a technology that realizes many human characteristics such as speaking, writing, learning, making analysis, etc. (IBM, 2024). AI technologies, with their computational speed and storage capacity, contribute to decision-making processes thanks to their capabilities in data analysis (Tsang & Lee, 2022). AI, designed to digitally imitate human intelligence (Huang & Rust, 2018), is defined as a machine that uses algorithms and statistics to perform human-specific functions. AI, derived from the idea that machines can think like humans (Zhang et al., 2021), enables systems to produce actions through intelligent processes using data collected from physical and virtual environments. It works with huge data and has emerged as the most fascinating technology developed in recent years (Chintalapati & Pandey, 2022). It differs from other information technologies because it can update itself through data while processing information for people's use (Huang & Rust, 2022). AI, which aims to artificially produce the intelligent behavior of creatures in nature, is used in different fields. As a result of developments in information and communication technologies, AI is used in many sectors such as automotive, manufacturing, law, health, education, and e-commerce, and provides various benefits (Davenport et al., 2020). Developments in this field are becoming vital for organizations and investments are reaching significant levels each day. While investments in this field already account for large shares, it would not be wrong to say that investments will continue to increase in the future.

To compete in the competitive global environment, investments must be made in the field of AI. Because it has comprehensive effects on both social and economic development and has become the driving force for industrial transformation (Zhang et al., 2023; Dong & Wang, 2023). Social development and development, manufacturing and production industry, environment, energy and natural resources, aviation and space, education, agriculture, finance, defense, health, human resources, e-government applications, e-commerce, culture, art, taxation, logistics, it is stated that it has application areas in all sectors such as tourism, sports, informatics, and communication (TBD, 2020). In the report of the Istanbul Chamber of Commerce Strategic Research Center, it is reported that venture capital investments in the field of AI on a global scale in 2021 reached 214 billion 782 million dollars and decreased to 124.9 billion dollars in 2022. The European Parliamentary Research Service (EPRS) document stated that the global AI market is valued at over $145 billion in 2023. The US and China are in the first place in investment in AI. It is stated that the EU will invest $2.35 billion in AI in the 2021-2027 period. (EPRS, 2024). It is seen that these investments will continue to increase in the future. It has been stated that in Türkiye, AI entry capital investments, which were 1.6 million dollars in 2020, amounted to 2 billion 81 million dollars in 2021. As a result of sectoral data in 2021, it was stated that media, robotics, and healthcare were among the sectors in which the most investments were made (İTOSAM, 2024). The rate of startups in Türkiye stating that they use any of the AI technologies will be 3.5% in 2022 and 5.5% in 2023. When the reasons why startups do not use AI are examined; it was stated that the most essential reason was that the costs were too high, with 60.7%. This was followed by the lack of relevant expertise in the initiative with 53.8% and incompatibility with existing equipment, software or systems with 49.6%, respectively (TÜİK, 2023). Therefore, it is very crucial for organizations or countries to constantly evaluate their efficiency and productivity to ensure their sustainability. In this context, Data Envelopment Analysis (DEA) is one of the important non-parametric methods that is widely applied (Wanke et al., 2016). The current study, it is expected that the evaluation of Türkiye AI performance for the 9 years between 2014 and 2022 will contribute to both the sector and policymakers.

The rest of the study is organized as follows. The second chapter includes a literature review. In the third section, the DEA method used in the research is explained and information about the input and output variables used in the analysis is included. The fourth section contains the analysis results. In the fifth chapter, a general evaluation of the study was made.

2. LITERATURE

DEA method is widely used in many different fields such as energy, technology, banking, agriculture, tourism, supply chain, transportation, education, manufacturing systems, aviation, and health. (Emrouznejad & Yang, 2018; Yu & He, 2020; Ersoy, 2021; Xiao et al., 2023; Yu & Rakshit, 2023; Pan et al., 2024; Oukil et al., 2024; Antunes et al., 2024). As in many sectors, there are studies carried out using the DEA method in the field of intelligent automation systems and AI. Azadeh et al. (2011) proposed an integrated approach to analyze the impact of personnel attributes of 102 branches of a bank operating in the private sector on branch efficiency. In the proposed algorithm, the impact of personnel productivity characteristics on total productivity is evaluated through DEA an Artificial Neural Network. Hu et al. (2019) used the DEA method in their study to evaluate the financial performance of 34 companies listed in the AI industry on China's Shanghai and Shenzhen stock exchanges. In the activity analysis, development capability, operational capability, solvency, and innovation capability were used as input variables and profitability was used as output variable. Gao et al. (2020) used the DEA method to evaluate the innovation effectiveness of 40 typical AI companies in China. According to the study results, the comprehensive efficiency is low, scale efficiency and pure technical efficiency are not high, and some enterprises have factors in redundancy.

Mirmozaffari et al. (2021) developed a method to analyze and evaluate the eco-efficiency determining factor of 22 local cement companies in Iran between 2015 and 2019. Two widely used AI approaches were used in the study. To achieve the purpose of the research, optimization DEA and machine learning algorithms were used in the first and second steps, respectively. After applying the proposed model, the Malmquist productivity index was computed to evaluate the productivity of companies over 2015–2019 period. Yu (2021) analyzed the theory of data envelopment and cloud edge computing in his study. He also applied this to intelligent robot development theory. In the study, the development trend of the intelligent social robot was analyzed from the perspectives of electrical engineering and data analytics. In the research, the basic direction of bionic robot design was established based on environmental analysis and examination of bionic robot products. Liu et al. (2022) examined the impact of AI on the energy efficiency of manufacturing enterprises. The research revealed several important findings. According to the research results, AI, measured by industrial robots, significantly increases the energy efficiency of manufacturing enterprises. According to the mechanism test, AI supports the improvement in energy efficiency by promoting technological progress. According to the heterogeneity analysis, it turns out that the age of manufacturing enterprises hinders the encouraging effect of AI on energy efficiency. Yen et al. (2023) investigated in their study how smart port design can affect the efficiency of maritime transportation with a three-step DEA-Tobit modelling approach. The top 20 international ports in the world, according to their production capacities, were used in the research. First, the operational efficiency of the ports was evaluated using the DEA method. In the research, automation, environment, and intelligence were determined as smart port design to investigate the effect of smart port design. The essentials of three different smart port designs were determined with the analytical hierarchy process. Finally, the Tobit regression model evaluated how weighted smart port features affect operating efficiency. Shi et al. (2024) used the DEA method in their study to effectively evaluate the effectiveness of the innovation of the regional AI industry to promote the allocation of resources and the development of the AI sector. There are three essential aspects of the results of this study. First, the AI industry in China has achieved improvements in scale efficiency and technical efficiency between 2015 and 2018. Secondly, China's AI industry shows inter-regional heterogeneity. Third, three environmental factors such as the level of economic development, government innovation support, and maturity of the technology market have an impact on innovation efficiency.

3. METHOD

3.1. Data Envelopment Analysis

DEA, a linear programming-based method, is used to evaluate the performance of decision-making units (Selamzade et al., 2023; Oukil et al., 2024; Pan et al., 2024; Dalir et al., 2024). DEA, introduced by Farrell (1957) in "Measurement of Productive Efficiency", was developed by Charnes et al. (1978). It is a nonparametric mathematical programming approach (Antunes et al., 2024; Oukil et al., 2024; Arunyanart, 2024). Banker, Charnes and Cooper (1984) then introduced the BCC model, which separates technical efficiency from scale efficiency. However, in the current study, efficiency evaluation was made using the input-oriented CCR model. The input-oriented CCR model (Cooper et al., 2011; Xu & Quenniche, 2012; Selamzade et al., 2023; Ersoy & Tehci, 2023) and the Super Efficiency (SE) CCR model (Seiford & Zhu, 1999: 175; Xu & Ouenniche, 2012; Ersoy and Tehci, 2023) can be seen in Table 1. The efficiency score must be "1" for DMUs to be efficient (Ersoy, 2021; Selamzade et al., 2023). When comparing the CCR and SE CCR models, it can be stated that the efficiency score of SE CCR can exceed 1, allowing efficient DMUs to be ranked, and DMUs with excessive inputs or outputs can be excluded from the analysis. In order to apply DEA, decision-making units with similar characteristics should be selected. In addition, previous studies in the literature have shown that the total number of decision-making units should generally be twice the total number of inputs and outputs (Çelik, 2016; Ersoy, 2021). In model (1) and model (2), x_{ij} denotes the amount of input *i* used by DMU_j and y_{rj} denotes the amount of output *r* produced by DMU_j. In model (1), $j = 1,...,n$ and θ_t refers to DMU_t whose efficiency is measured. If the optimal value of θ_t is equal to 1, then DMU_t under evaluation is efficient; else, *θ_t <1 indicates that DMU_t is inefficient. In model (2), θ_t <1 indicates that DMU_t is inefficient; else, efficient DMU_s will have a $\theta_t \geq 1$* (Ersoy, 2021).

Table 1. Input-Oriented CCR Model and SE-CCR Model

Classic input-oriented CCR Model	Input-oriented SE-CCR Model

$$\begin{aligned} &\min \theta_t \\ &s.t. \\ &\sum_{j=1}^{n} \lambda_j x_{ij} \le \theta_t x_{it}, \;\; i = 1,\ldots,m \\ &\sum_{j=1}^{n} \lambda_j y_{rj} \ge y_{rt}, \;\; r = 1,\ldots,s \\ &\lambda_j \ge 0, \;\; j = 1,\ldots,n \end{aligned} \tag{1}$$

$$\begin{aligned} &\min \theta_t \\ &s.t. \\ &\sum_{\substack{j=1 \\ j \ne t}}^{n} \lambda_j x_{ij} \le \theta_t x_{it}, \;\; i = 1,\ldots,m \\ &\sum_{\substack{j=1 \\ j \ne t}}^{n} \lambda_j y_{rj} \ge y_{rt}, \;\; r = 1,\ldots,s \\ &\lambda_j \ge 0, \;\; j = 1,\ldots,n \end{aligned} \tag{2}$$

3.2. Data and Variables

The input and output variables used in the study were obtained from the 2024 report on AI prepared by the Istanbul Chamber of Commerce Strategic Research Center (İTOSAM, 2024). Venture capital investments in AI (Million Dollars) and Number of companies developing AI in Türkiye were used as input variables in the study. Number of industrial robot installations and Number of industrial robot stocks were used as output variables in the study. Statistics regarding the input and output variables used in the research are shown in Table 2, and the correlation between input and output variables is shown in Table 3. AI is a new and developing field. Therefore, due to the limited data and scarcity of sectoral reports in the field of AI in Türkiye, effectiveness analyses were conducted with limited data.

Table 2. Statistical Indicators of Input and Output Variables for 2014-2022

	Venture capital investments in AI (Million Dollars)	**Number of companies developing AI in Türkiye**	**Number of industrial robot installations**	**Number of industrial robot stocks**
Max	2081	860	3748	22735
Min	1	152	1246	6286
Average	263.67	422.89	2193.33	13626.33
Std deviation	687.00	246.69	762.91	5371.22

Table 3. Correlation Relationship Between Input and Output Variables

	Venture capital investments in AI (Million Dollars)	**Number of companies developing AI in Türkiye**	**Number of industrial robot installations**	**Number of industrial robot stocks**
Venture capital investments in AI (Million Dollars)	1			
Number of companies developing AI in Türkiye	0.537	1		
Number of industrial robot installations	0.532	0.897	1	
Number of industrial robot stocks	0.483	0.983	0.899	1

The first two columns of Table 2 include the input variables. The third and fourth columns of Table 2 include the output variables. The first row of Table 2 contains the maximum values of the input and output variables, while the other rows contain their minimum values, mean values, and standard deviations, respectively. Table 3 includes the statistical representation of the correlation of input and output variables. It is understood from Table 3 that the highest correlation value is 0.983 between the output variable "Number of industrial robot stocks" and the input variable "Number of companies developing AI in Türkiye".

4. RESULTS

DEA analysis was carried out using the EMS 1.3.0 package program. The results of the effectiveness analysis for the CCR DEA model and SE-CCR DEA model are given in Table 4.

Table 4. Efficiency Scores

DMU	CCR	SE-CCR
2014	1.000	1.219
2015	1.000	1.101
2016	0.964	0.964
2017	0.973	0.973
2018	1.000	1.027
2019	0.807	0.807
2020	1.000	1.220
2021	0.641	0.641
2022	0.629	0.629

In the second column of Table 4, there are CCR effectiveness scores, and in the third column, there are SE-CCR scores. According to the effectiveness scores in Table 4, 2014, 2015, 2018, and 2020 were effective. Efficient years are ranked among themselves according to their SE-CCR efficiency scores. Among the effective years, 2020 was determined to be the most effective DMU with an efficiency score of 1,220. For DMUs that are not effective to become effective, some potential improvement suggestions need to be presented. Potential improvement suggestions for inefficient years are shown in Table 5.

Table 5. Potential Improvement Suggestions for Inefficient Years

Year	Efficiency Score	Variable	Original Value	Projected Value	Difference	Rate
2016	0.96	Number of industrial robot installations	1840	2168.422	328.4224	17.85
		Number of industrial robot stocks	9756	10120.03	364.0334	3.73
2017	0.97	Number of industrial robot installations	2050	2415.444	365.444	17.83
		Number of industrial robot stocks	11599	11918.916	319.916	2.76
2019	0.81	Number of industrial robot installations	1807	3982.983	2175.983	120.42
		Number of industrial robot stocks	15033	18634.869	3601.869	23.96
2021	0.64	Number of industrial robot installations	3070	6477.196	3407.196	110.98
		Number of industrial robot stocks	19325	30163.598	10838.6	56.09
2022	0.63	Number of industrial robot installations	3748	7758.201	4010.201	107.00
		Number of industrial robot stocks	22735	36129.101	13394.1	58.91

Table 5 shows the efficiency score for 2017 as 0.97. For 2017 to be effective, it is recommended that the number of industrial robot installations be 2415.44 and the number of industrial robot stocks be 11918.916. Similarly, potential improvement suggestions for other inefficient years are given in Table 5. It was evaluated with the scores as given in Table 4.

5. DISCUSSION AND CONCLUSION

Due to the increase in labor costs in developed countries, most of the international companies operating in these countries have shifted their production to developing countries. Smart automation systems can make production more flexible, as well as reduce the role of the workforce in the production process. Thus, developing countries have begun to lose their biggest competitive advantage against smart automation systems. One of the main reasons why developed countries ensure the widespread use of smart automation technologies is to prevent the development of other countries, especially China. Intelligent automation systems and AI are used by developed countries to bring industrial investments back to their lands. Thus, intelligent automation systems and AI are used as tools by developed countries to both compete economically and protect their national interests against developing countries (İTOSAM, 2024). When evaluated from this perspective, it is essential to evaluate the effectiveness of intelligent automation systems and AI sectors in developed and developing countries. It can be said that national studies on AI in general are primarily conducted in the fields of logistics (Aylak et al., 2021), healthcare (Keleş, 2022), education (İşler and Kılıç, 2021), and human resource management (Gür et al., 2019). China has garnered significant attention in research related to the AI sector. Factors such as the economic development level of countries, governmental support, and the maturity of the technology market (Shi et al., 2024), increasing R&D investments, and excavating high-quality scientific research (Dong & Wang, 2023), are believed to enhance effectiveness in this industry. Lyu and Cui (2024) assessed the financial performance of Chinese AI companies from 2018 to 2022. Their findings indicate that these companies generally performed well financially and exhibited potential for improvement, as well as a consistent growth trend. These insights can be interpreted as general recommendations. Consequently, similar recommendations can be made for evaluating the effectiveness of the current study.

In this study, the effectiveness of the AI sector in Türkiye was evaluated yearly. In the research, efficiency analysis was conducted using the DEA method. Input-oriented CCR model and super efficiency model were used for efficiency measurement. According to DEA activity results, Türkiye was found effective in 2014, 2015, 2018 and 2020. The ranking of the efficient years among themselves was made according to the results of the super-efficiency CCR model, and the most effective year was determined to be 2020. Globally, it is also seen in the reports that AI investments increased in 2021 and decreased in the following few years. It can be said that this is parallel to the national economies. Therefore, reasons such as high costs and lack of relevant experts may cause low efficiency in recent years. However, it can be said that it is promising for the coming years. Additionally, potential improvement suggestions for ineffective years are included in the findings section of the study. Since research results depend on the input and output variables used in the analysis, changes in the input and output variables may affect the analysis results. When evaluated from this perspective, it is useful to remember that the efficiency results obtained with DEA are relative. Like many other studies, this one has certain limitations. One of the limitations of the study is that the research only covers Türkiye. Another key limitation is that the DEA analysis was conducted using only two inputs and two outputs. Another limitation is that years were used as DMU in the study. In future studies, efficiency measurements can be made using different input and output variables in different sectors such as tourism, energy, agriculture, health, education and manufacturing. Additionally, studies can be conducted using multi-criteria decision-making methods such as TOPSIS, EDAS, CODAS, AHP, VIKOR, Fuzzy AHP, Fuzzy TOPSIS, Fuzzy VIKOR or different methods in addition to the DEA method. This study emphasizes the importance of using AI effectively. The research results may guide public and private sector representatives in the field of AI.

References

Antunes, J., Hadi-Vencheh, A., Jamshidi, A., Tan, Y., Wanke, P. (2024). Cost efficiency of Chinese banks: Evidence from DEA and MLP-SSRP analysis. Expert Systems with Applications, 237. https://doi.org/10.1016/j.eswa.2023.121432

Arunyanart, S. (2024). Performance evaluation of facility locations using integrated DEA-based techniques. Heliyon, 10, https://doi.org/10.1016/j.heliyon.2024.e32430

Aylak, B. L., Oral, O., Yazıcı K. (2021). Using Artificial Intelligence and Machine Learning Applications in Logistics. El-Cezerî Journal of Science and Engineering, 8(1), 74-93. https://doi.org/10.31202/ecjse.776314

Azadeh, A., Saberi, M., Moghaddam, R.T., Javanmardi, L. (2011). An integrated Data Envelopment Analysis–Artificial Neural Network–Rough Set Algorithm for assessment of personnel efficiency. Expert Systems with Applications, 38(3), 1364-1373.https://doi.org/10.1016/j.eswa.2010.07.033

Banker, R.D., A. Charnes, W.W. Cooper (1984). Models for Estimating Technical and Scale Efficiencies. Management Science, 30(9), 1078-1092. https://doi.org/10.1287/mnsc.30.9.1078

Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision making units. European journal of operational research, 2(6), 429-444. https://doi.org/10.1016/0377-2217(78)90138-8

Chintalapati, S., Pandey, S. K. (2022). Artificial intelligence in marketing: A systematic literature review. International Journal of Market Research, 64(1), 38-68. https://doi.org/10.1177/14707853211018428

Cooper, W.W., Seiford, L.M., and Zhu, J. (2011). Data envelopment analysis: History, models, and interpretations. In W. Cooper, L. Seiford, & J. Zhu (Eds.), Handbook on data envelopment analysis. Springer

Çelik, M.K. (2016). Evaluating the Efficiency of Business in Tourism Sector with Data Envelopment Analysis. Uluslararası İktisadi ve İdari İncelemeler Dergisi, 17, 65-88. https://doi.org/10.18092/ijeas.58275

Dalir, O., Torabi, T., Rabiei, M., Jahromi, Y.M. (2024). Application of data envelopment analysis in determining the efficiency of management and company. International Journal of Nonlinear Analysis and Applications (IJNAA), 15(6), 237-243. http://dx.doi.org/10.22075/ijnaa.2023.31175.4582

Davenport, T., Guha, A., Grewal, D., Bressgott, T. (2020). How artificial intelligence will change the future of marketing. Journal of the Academy of Marketing Science, 48, 24-42. https://doi.org/10.1007/s11747-019-00696-0

Dong, Y., Wang, D. (2023). China's artificial intelligence efficiency and its influencing factors: Based on DEA-Malmquist and Tobit regression model. Decision Science Letters, 12(4), 729-738. https://doi.org/10.5267/j.dsl.2023.7.003

Emrouznejad, A., Yang, G-L. (2018). A survey and analysis of the first 40 years of scholarly literature in DEA: 1978–2016. Socio-Economic Planning Sciences, 61, 4-8. https://doi.org/10.1016/j.seps.2017.01.008

EPRS (2024). https://www.europarl.europa.eu/RegData/etudes/ATAG/2024/760392/EPRS_ATA(2024)760392_EN.pdf Accessed 27.09.2024

Ersoy, Y. (2021). Performance Evaluation in Distance Education by Using Data Envelopment Analysis (DEA) and TOPSIS Methods. Arabian Journal for Science and Engineering, 46, 1803-1807. https://doi.org/10.1007/s13369-020-05087-0

Ersoy, Y., Tehci, A. (2023). Efficiency Evaluation of Energy Companies with Data Envelopment Analysis. The Journal of International Scientific Researches, 8(3), 360-366. https://doi.org/10.23834/isrjournal.1331147

Farrell, M. J. (1957). The measurement of productive efficiency. Journal of the Royal Statistical Society: Series A (General), 120(3), 253-290. https://doi.org/10.2307/2343100

Gao, X., Yang, Z., Sun, Z. (2020). Research on the Innovation Efficiency of Artificial Intelligence Enterprise Based on DEA Method. Advances in Economics, Business and Management Research, Atlantis Press, 133, 1-6. https://doi.org/10.2991/aebmr.k.200402.001

Gür, Y. E., Ayden, C., & Yücel, A. (2019). Effects to Human Resources Managements of Developments in Artificial Intelligence. Firat University International Journal of Economics and Administrative Sciences, 3(2), 137-158.

Hu, J., Nian, Z., & Wang, X. (2019). Research on financial performance evaluation on artificial intelligence listed companies in China based on DEA method. 2019 Portland International Conference on Management of Engineering and Technology (PICMET), 1-6, IEEE. https://doi.org/10.23919/PICMET.2019.8893931

Huang, M. H., Rust, R. T. (2018). Artificial intelligence in service. Journal of Service Research, 21(2), 155-172. https://doi.org/10.1177/1094670517752459

Huang, M. H., Rust, R. T. (2022). A framework for collaborative artificial intelligence in marketing. Journal of Retailing, 98(2), 209-223. https://doi.org/10.1016/j.jretai.2021.03.001

IBM (2024). https://www.ibm.com/topics/artificial-intelligence Accessed 12.07.2024

İTOSAM, (2024). Akıllı Otomasyon Çağında Ulusların Rekabeti: Yapay, Zeka, Robotlar ve Gelişen Ülkeler, İTO Sektörel Araştırmalar Yayın NO: 2024-18, İstanbul. 1-94. https://itosam.org.tr/duyuru/itosamdan-yeni-rapor-pdtv, Accessed 12/06/2024

İşler, B., & Kılıç, M.Y (2021). The Use and Development of Artificial Intelligence in Education 5(1), 1-11. https://doi.org/10.17932/IAU.EJNM.25480200.2021/ejnm_v5i1001

Keleş, H. (2022). Artificial Intelligence Applications in Medicine. Journal of Kırıkkale University Faculty of Medicine, 24(3), 604-613. https://doi.org/10.24938/kutfd.1214512

Liu, J., Qian, Y., Yang, Y., Yang, Z. (2022). Can Artificial Intelligence Improve the Energy Efficiency of Manufacturing Companies? Evidence from China. International Journal of Environmental Resarch and Public Health, 19(4), 1-18. https://doi.org/10.3390/ijerph19042091

Lyu, R., & Cui, C. (2024). A Study on the Financial Performance of Chinese Artificial Intelligence Listed Companies Based on the DEA-Malmquist Model. Highlights in Science, Engineering and Technology, 98, 452-462. https://doi.org/10.54097/mrqzrx17

Mirmozaffari, M., Shadkam, E., Khalili, S.M., Kabirifar, K., Yazdani, R., Gashteroodkhani, T.A. (2021). A novel artificial intelligent approach: comparison of machine learning tools and algorithms based on optimization DEA Malmquist productivity index for eco-efficiency evaluation. International Journal of Energy Sector Management, 15(3), 523-550. https://doi.org/10.1108/IJESM-02-2020-0003

Oukil, A., Kennedy, R.E., Al-Hajri, A., Soltani, A.A. (2024). Unveiling the potential of hotel mergers: A hybrid DEA approach for optimizing sector-wide performance in the hospitality industry. International Journal of Hospitality Management, 116, https://doi.org/10.1016/j.ijhm.2023.103620

Öztemel, E. (2020). Yapay Zekâ ve İnsanlığın Geleceği. TÜBA-Bilişim Teknolojileri ve İletişim Çalışma Grubu Bilişim Teknolojisi ve İletişim: İnternet ve Toplumsal Etkileri Çalıştayı, 77-90. https://doi.org/10.53478/TUBA.2020.011

Pan, Y., Zhang, C-C., Lee, C-C., Lv, S. (2024). Environmental performance evaluation of electric enterprises during a power crisis: Evidence from DEA methods and AI prediction algorithms. Energy Economics, 130, https://doi.org/10.1016/j.eneco.2023.107285

Seiford, L.M, Zhu, J. (1999). Infeasibility of super-efficiency data envelopment analysis models. INFOR: Information Systems and Operational Research, 37(2), 174–187. https://doi.org/10.1080/03155986.1999.11732379

Selamzade, F., Ersoy, Y., Ozdemir, Y., Celik, M.Y. (2023). Health Efficiency Measurement of OECD Countries Against the COVID-19 Pandemic by Using DEA and MCDM Methods. Arabian Journal for Science and Engineering, 48(11), 15695-15712. https://doi.org/10.1007/s13369-023-08114-y

Shi, J., Mei, J., Zhu, L., Wang, Y. (2024). Estimating the Innovation Efficiency of the Artificial Intelligence Industry in China Based on the Three-Stage DEA Model. IEEE Transactions on Engineering Management, 71, 9217-9228. https://doi.org/10.1109/TEM.2023.3323292

TBD, (2020). Türkiye'de Yapay Zekânın Gelişimi için Görüşler ve Öneriler, Türkiye Bilişim Derneği Kavramsal Rapor https://www.tbd.org.tr/pdf/yapay-zeka-raporu.pdf

Tsang, Y. P., & Lee, C. K. M. (2022). Artificial intelligence in industrial design: A semi-automated literature survey. Engineering Applications of Artificial Intelligence, 112, 104884. https://doi.org/10.1016/j.engappai.2022.104884

TÜİK (2023). https://data.tuik.gov.tr/Bulten/Index?p=Girisimlerde-Bilisim-Teknolojileri-Kullanim-Arastirmasi-2023-49393 Accessed 15.07.2024

Xiao, K., Ullah, W., Fu, J., Zhang, X. (2023). Poverty Alleviation Efficiency of Tourism and Its Spatiotemporal Differentiation in Jiangxi Province of China Based on the DEA Model. Sage Open, 13(2). https://doi.org/10.1177/21582440231168835

Xu, B., Ouenniche, J. (2012) A data envelopment analysis-based framework for the relative performance evaluation of competing crude oil prices volatility forecasting models. Energy Economics, 34(2), 576–583. https://doi.org/10.1016/j.eneco.2011.12.005

Wanke, P., Azad, M. A. K., Barros, C. P. (2016). Predicting efficiency in Malaysian Islamic banks: A two-stage TOPSIS and neural networks approach. Research in International Business and Finance, 36, 485-498. https://doi.org/10.1016/j.ribaf.2015.10.002

Yen, B.T.H., Huang, M-J., Lai, H-J., Cho, H-H., Huang, Y-L. (2023). How smart port design influences port efficiency-A DEA-Tobit approach. Research in Transportation Business & Management, 46, 1-12. https://doi.org/10.1016/j.rtbm.2022.100862

Yu, D., He, X. (2020). A bibliometric study for DEA applied to energy efficiency: Trends and future challenges. Applied Energy, 268, https://doi.org/10.1016/j.apenergy.2020.115048

Yu, M-M., Rakshit, I. (2023). An alternative assessment approach to global logistics performance evaluation: Common weight H-DEA approach. International Transaction in Operational Research, 1-24. https://doi.org/10.1111/itor.13360

Yu, S. (2021). Cloud edge computing for socialization robot based on intelligent data envelopment. Computers & Electrical Engineering, 92, 1-12. https://doi.org/10.1016/j.compeleceng.2021.107136

Zhang, Q., Lu, J., Jin, Y. (2021). Artificial intelligence in recommender systems. Complex & Intelligent Systems, 7(1), 439-457. https://doi.org/10.1007/s40747-020-00212-w

Zhang, B., Zhu, J., & Su, H. (2023). Toward the third generation artificial intelligence. Science China Information Sciences, 66(2), 121101. https://doi.org/10.1007/s11432-021-3449-x