



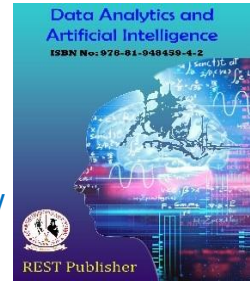
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Evaluating Artificial Intelligence Technologies in Healthcare Using the EDAS Method

Prabhakar Vagvala

Alcon, Director and Head of Global ERP Operations, Dallas-Fort Worth Metroplex, USA.

Corresponding author: vipinprabhakar@gmail.com

Abstract: The rapid advancement of Artificial Intelligence (AI) in healthcare has led to the adoption of diverse technologies aimed at improving accuracy, efficiency, and cost-effectiveness. This study applies the Evaluation Based on Distance from Average Solution (EDAS) method to evaluate and rank six prominent AI technologies in healthcare: AI-Powered Diagnosis (AID), Robotic Surgery (RS), Clinical Decision Support Systems (CDSS), Patient Monitoring Systems (PMS), AI-Based Drug Discovery (AIDD), and Chatbots for Patient Interaction (CPI). The technologies were assessed using four evaluation parameters: Accuracy (%), Cost Savings (%), Time Efficiency (%), and Training (Hours) with equal weighting assigned to each criterion. The results indicate that Chatbots for Patient Interaction (CPI) rank first due to their superior performance in training efficiency and time optimization, making them ideal for rapid deployment and scalability in healthcare settings. Patient Monitoring Systems (PMS) secured second place, demonstrating a balanced performance across cost savings and operational efficiency. Clinical Decision Support Systems (CDSS) ranked third, largely benefiting from their streamlined training requirements. AI-Based Drug Discovery (AIDD) followed closely, ranking fourth due to significant cost-saving advantages and moderate time efficiency. AI-Powered Diagnosis (AID) ranked fifth, primarily excelling in accuracy but underperforming in other parameters. Finally, Robotic Surgery (RS) ranked last (sixth) despite achieving the highest accuracy, as its extensive training requirements and relatively limited cost efficiency impacted its overall performance. This study highlights the effectiveness of the EDAS method as a multi-criteria decision-making framework, enabling a comprehensive evaluation of AI technologies in healthcare. The rankings emphasize the trade-offs among accuracy, cost, efficiency, and ease of implementation, offering valuable insights for healthcare stakeholders to prioritize AI solutions that align with their operational needs and resource constraints. Future research can further refine this approach by integrating additional criteria or dynamic weight assignments to reflect varying healthcare priorities.

Keywords: Artificial Intelligence in Healthcare, EDAS Method, Multi-Criteria Decision Making (MCDM), AI Technology Evaluation, Healthcare Efficiency, AI Performance Ranking.

1. INTRODUCTION

Artificial Intelligence (AI) has emerged as a transformative force across various industries, with healthcare being one of the most significant beneficiaries. The continuous rise in patient data, advancements in computational power, and increasing demands for efficient, cost-effective healthcare solutions have motivated researchers and healthcare providers to adopt AI-driven technologies. The healthcare sector faces critical challenges, such as rising costs, inconsistent quality of care, medical errors, and the overwhelming volume of patient data. These issues have necessitated the adoption of innovative technologies that can enhance precision, efficiency, and overall effectiveness. AI technologies are uniquely suited to address these challenges, offering tools that automate processes, reduce administrative burdens, and assist clinicians in diagnostics, prognosis, treatment planning, and drug discovery. AI has proven to be a pivotal technology in analyzing medical images, predicting disease progression, identifying patterns in clinical data, and personalizing treatment strategies. For instance, deep learning algorithms in medical imaging outperform traditional techniques in detecting anomalies in radiological scans, while

machine learning models offer accurate predictions for disease outbreaks, cancer diagnoses, and patient readmissions. Numerous applications that transform clinical research, operational effectiveness, and patient care are part of the diverse use of AI in healthcare. **AI-Powered Diagnostics** AI algorithms have transformed diagnostic capabilities by improving accuracy and early detection of diseases. Machine learning models trained on medical imaging datasets, such as X-rays, CT scans, and MRIs, can detect abnormalities such as tumors, fractures, and infections with precision. For example, AI-based tools such as IBM Watson and Google's DeepMind have demonstrated exceptional accuracy in diagnosing cancers, diabetic retinopathy, and neurological disorders. AI minimizes the risks of human errors, reduces diagnostic delays, and provides decision support to clinicians. **Robotic Surgery** AI-powered robotic surgical systems, such as the da Vinci Surgical System, have advanced minimally invasive procedures by providing enhanced dexterity, precision, and visualization. These systems assist surgeons with complex tasks, enabling smaller incisions, faster recovery times, and reduced complications. AI-driven robotic systems leverage real-time data analysis, sensor feedback, and machine learning to optimize surgical techniques and ensure patient safety. **Systems for Clinical Decision Support (CDSS)** In order to give medical practitioners evidence-based suggestions, systems that support clinical decisions use artificial intelligence (AI) to evaluate large datasets, such as genomic data, laboratory results, and electronic health records (EHRs). CDSS assists in diagnosis, treatment selection, and outcome prediction, thereby improving clinical decision-making. For example, AI-powered systems can predict sepsis risks, recommend medication adjustments, and alert clinicians about potential drug interactions. **Systems for Monitoring Patients** Vital signs including heartbeat, blood pressure, pulse, and oxygen levels are continuously monitored by AI-enabled monitoring systems in order to spot significant abnormalities and send out appropriate alerts. Wearable devices and Internet of Things (IoT) technologies equipped with AI algorithms enable remote patient monitoring, facilitating early intervention and reducing hospital readmissions. These systems are particularly beneficial for managing chronic diseases, such as diabetes and cardiovascular conditions. **AI-Based Drug Discovery** Traditional drug discovery is a time-consuming and expensive process that often spans several years. AI accelerates drug discovery by analyzing molecular structures, identifying potential drug candidates, and predicting their efficacy. AI-based platforms use deep learning and molecular modeling to shorten development timelines and reduce costs. Companies such as Benevolent AI and Insilico Medicine have successfully applied AI to discover novel drug compounds and repurpose existing medications for diseases like COVID-19 and rare genetic disorders. **Chatbots for Patient Interaction** AI-powered chatbots play a significant role in enhancing patient engagement, streamlining communication, and delivering information. These chatbots assist patients with scheduling appointments, answering queries, monitoring symptoms, and providing guidance based on pre-programmed algorithms. Chatbots reduce the workload on healthcare staff, improve accessibility to healthcare services, and empower patients to take control of their health.

2. BENEFITS OF AI IN HEALTHCARE

The adoption of AI in healthcare brings numerous benefits that address longstanding challenges and deliver improved patient outcomes. Key advantages include:

- **Improved Diagnostic Accuracy:** AI algorithms offer superior accuracy in detecting diseases, reducing misdiagnoses and enabling early intervention.
- **Cost Savings:** Automation of routine tasks, optimization of workflows, and early disease detection help reduce operational costs.
- **Enhanced Efficiency:** AI streamlines administrative tasks, accelerates clinical decision-making, and improves resource utilization.
- **Personalized Treatment:** AI facilitates precision medicine by analyzing patient-specific data to recommend tailored treatment plans.
- **Reduced Burden on Clinicians:** AI minimizes clinician fatigue by automating repetitive tasks, such as documentation, data entry, and patient monitoring.
- **Improved Access to Care:** AI technologies, such as telemedicine and chatbots, improve healthcare access, particularly in remote and underserved areas.

To objectively assess the performance of AI technologies in healthcare, evaluation methods such as the Evaluation based on Distance from Average Solution (EDAS) method are employed. In healthcare, it evaluates multiple

criteria, such as accuracy, cost savings, time efficiency, and training requirements, to identify the most effective AI solutions. For example, an EDAS analysis of six healthcare technologies—AI-Powered Diagnosis, Robotic Surgery, Clinical Decision Support Systems, Patient Monitoring Systems, AI-Based Drug Discovery, and Chatbots for Patient Interaction—demonstrates trade-offs between benefits and limitations. Technologies such as Chatbots may excel in training efficiency but underperform in accuracy, while Robotic Surgery achieves high accuracy but requires significant training hours. The EDAS method aids in identifying optimal solutions based on stakeholder priorities and performance metrics. Artificial Intelligence has revolutionized the healthcare sector by offering innovative tools to address complex challenges and improve patient outcomes. From enhancing diagnostic accuracy to accelerating drug discovery and enabling remote monitoring, AI technologies are reshaping the future of healthcare. The integration of AI ensures cost-effective, precise, and efficient healthcare delivery, benefiting patients, clinicians, and healthcare providers alike. However, challenges related to data privacy, ethics, and integration remain, necessitating continuous efforts to address these limitations. Through systematic evaluation methods like EDAS, stakeholders can assess the strengths and weaknesses of AI technologies, enabling informed decision-making and strategic implementation. As AI continues to advance, its transformative potential in healthcare will unlock new opportunities for improving global health outcomes and ensuring equitable access to quality care. This research explores the performance, challenges, and opportunities of AI in healthcare, providing insights into its role as a catalyst for sustainable healthcare innovation.

3. MATERIALS & METHODS

The healthcare sector is only one of several areas that artificial intelligence (AI) has transformed. Its incorporation into healthcare systems may enhance the effectiveness, precision, and general caliber of patient treatment. From assisting in diagnostics to personalizing treatment plans, AI technologies are reshaping traditional healthcare practices. However, evaluating these technologies to determine their suitability for specific healthcare applications is a multifaceted process. One of the prominent methodologies for assessing and ranking alternatives based on multiple criteria is the Evaluation Based on Distance from Average Solution (EDAS) method. This paper delves into the application of the EDAS method to evaluate AI solutions in healthcare, highlighting its practicality and significance in decision-making. Healthcare systems globally are under immense pressure to provide quality care at affordable costs while addressing growing demands. AI technologies have emerged as a vital tool to meet these challenges, offering solutions ranging from predictive analytics to automated patient monitoring. Factors such as cost, accuracy, efficiency, and patient satisfaction must be carefully weighed against potential risks like data privacy concerns and high maintenance costs. This multidimensional evaluation requires robust decision-making tools, and the EDAS method stands out as a reliable choice. A multi-criteria decision-making technique, the EDAS method assesses options according to how far apart they are from the average solution. Unlike other MCDM methods that focus solely on the ideal or worst-case solutions, EDAS considers the average performance of alternatives as a benchmark. This approach offers a balanced evaluation framework, making it particularly useful in scenarios like healthcare, where trade-offs between competing criteria are inevitable. By computing two measures—Positive Distance from Average (PDA) and Negative Distance from Average (NDA)—EDAS quantifies the relative performance of alternatives and facilitates objective ranking. In applying the EDAS method to evaluate AI technologies in healthcare, the first step involves defining the alternatives and evaluation criteria. In this context, the alternatives can represent various AI applications, such as AI-powered diagnostics, robotic surgery, clinical decision support systems (CDSS), patient monitoring systems, AI-driven drug discovery, and chatbots for patient interaction. The evaluation criteria must reflect both the benefits and challenges of adopting these technologies. For instance, benefit criteria could include accuracy, time efficiency, and cost savings, while non-benefit criteria could encompass training requirements. The next step is to collect data for each alternative against the defined criteria. This data serves as the input for calculating the average values of each criterion across all alternatives. In the EDAS method, the PDA and NDA scores are calculated for each alternative by comparing their performance with the average criterion value. The PDA score represents the extent to which an alternative outperforms the average solution, while the NDA score indicates the degree to which it underperforms. These scores are then aggregated into a comprehensive evaluation score, which forms the basis for ranking the alternatives. For instance, AI-powered diagnostic systems (AID) achieve high accuracy (95.00%) and time efficiency (80.00%) but require moderate training efforts (40.00 hours). Robotic surgery (RS) ranks the highest in accuracy (98.00%) and time efficiency (85.00%) but involves the highest training requirement (80.00 hours). Similarly, clinical decision support systems (CDSS) exhibit a balance of moderate accuracy (92.00%) and cost savings (40.00%) but demand the least training

effort (20.00 hours). On the other hand, chatbots for patient interaction (CPI) score the lowest in accuracy (85.00%) and time efficiency (60.00%) but offer the lowest training requirements (10.00 hours), making them an affordable and accessible solution. A case study application of the EDAS method in healthcare can illustrate its utility. Consider the dataset in Table 1, where alternatives are evaluated against the specified criteria. After collecting the data and normalizing it, the PDA and NDA scores are calculated for each technology. For instance, AI-powered diagnostics may have a higher PDA for accuracy and time efficiency but a higher NDA for training requirements compared to chatbots for patient interaction. Similarly, robotic surgery, while excelling in accuracy and cost savings, may have a significant NDA score for its high training requirements. By systematically analyzing each alternative through EDAS, healthcare decision-makers can prioritize technologies that align with their strategic goals and resource constraints. For example, a hospital aiming to improve diagnostic precision might prioritize AI-powered diagnostics despite its training needs, while a clinic focusing on cost-effective patient interaction might lean toward chatbots. The EDAS method's ability to account for both benefit and non-benefit criteria ensures a comprehensive evaluation, enabling stakeholders to make informed decisions. One of the significant benefits of using EDAS in healthcare decision-making is its transparency. The method's reliance on average solutions as a benchmark ensures that all alternatives are judged on a common ground. This characteristic minimizes biases and promotes fairness in evaluations. Moreover, EDAS's mathematical simplicity allows for easy implementation and interpretation, making it accessible to healthcare administrators and policymakers without requiring extensive technical expertise. Despite its advantages, the EDAS method has some limitations. Its reliance on average solutions may lead to skewed results if the dataset contains outliers or significant variations among alternatives. To address this issue, careful preprocessing of data and sensitivity analysis are recommended. Additionally, the selection of criteria weights plays a critical role in the EDAS method. Assigning appropriate weights requires input from domain experts and stakeholders to ensure that the evaluation reflects real-world priorities. The application of EDAS in healthcare extends beyond evaluating AI technologies. It is also useful to evaluate other breakthroughs, like digital health records, wearable medical technology, and telemedicine platforms. The approach is a useful tool for negotiating the intricacies of healthcare decision-making because of its versatility and flexibility. The systematic evaluation framework like EDAS are becoming more and more necessary as AI usage in healthcare keeps growing. Moreover, integrating EDAS with other decision-making tools can enhance its effectiveness. For instance, combining EDAS with the Analytical Hierarchy Process (AHP) can help determine criteria weights based on stakeholder preferences, while pairing it with the Technique for Order Preference by Similarity to Ideal Solution) can validate the rankings generated by EDAS. Such hybrid approaches can provide more robust and comprehensive evaluations, particularly in high-stakes sectors like healthcare. The future of AI in healthcare hinges on its ability to deliver measurable benefits while addressing ethical and practical concerns. Decision-making frameworks like EDAS play a pivotal role in achieving this balance. By providing a structured approach to evaluating AI solutions, EDAS enables healthcare organizations to make informed choices that maximize value and minimize risks. As a result, patients, providers, and policymakers alike can benefit from the thoughtful integration of AI into healthcare systems. The Evaluation Based on Distance from Average Solution (EDAS) method offers a systematic and balanced approach to evaluating AI technologies in healthcare. Its focus on average solutions as a benchmark ensures fair and comprehensive assessments, making it particularly suitable for the multifaceted nature of healthcare decision-making. By applying EDAS to the dataset provided, stakeholders can identify AI solutions that align with their priorities, optimize resource allocation, and ultimately enhance patient outcomes. As healthcare systems continue to embrace AI, methods like EDAS will remain indispensable in guiding the adoption of these transformative technologies.

4. RESULT AND DISCUSSION

TABLE 1. Artificial Intelligence in Healthcare Data set

DATA SET				
	Accuracy (%)	Cost Savings (%)	Time Efficiency (%)	Training (Hours)
AI-Powered Diagnosis (AID)	95.00	50.00	80.00	40.00
Robotic Surgery (RS)	98.00	60.00	85.00	80.00
Clinical Decision Support Systems (CDSS)	92.00	40.00	75.00	20.00
Patient Monitoring Systems (PMS)	90.00	55.00	70.00	30.00
AI-Based Drug Discovery (AIDD)	89.00	70.00	65.00	50.00
Chatbots for Patient Interaction (CPI)	85.00	30.00	60.00	10.00

Table 1 presents a dataset for evaluating six artificial intelligence (AI) technologies in healthcare using the Evaluation Based on Distance from Average Solution (EDAS) method. The alternatives include AI-Powered Diagnosis (AID), Robotic Surgery (RS), Clinical Decision Support Systems (CDSS), Patient Monitoring Systems (PMS), AI-Based Drug Discovery (AIDD), and Chatbots for Patient Interaction (CPI). These technologies are assessed across four criteria: Accuracy (%), Cost Savings (%), Time Efficiency (%), and Training (Hours). Robotic Surgery demonstrates the highest accuracy (98%) and time efficiency (85%), albeit with the most extensive training requirement (80 hours). AI-Powered Diagnosis achieves a balance with high accuracy (95%) and time efficiency (80%) but moderate training needs (40 hours). Conversely, Chatbots for Patient Interaction exhibit the lowest accuracy (85%) and time efficiency (60%) yet excel with minimal training requirements (10 hours). AI-Based Drug Discovery offers the highest cost savings (70%) but comparatively lower accuracy (89%) and time efficiency (65%). The dataset highlights the trade-offs among these technologies, underscoring the importance of a multi-criteria decision-making framework like EDAS to objectively rank alternatives based on their performance across diverse parameters critical to healthcare stakeholders.

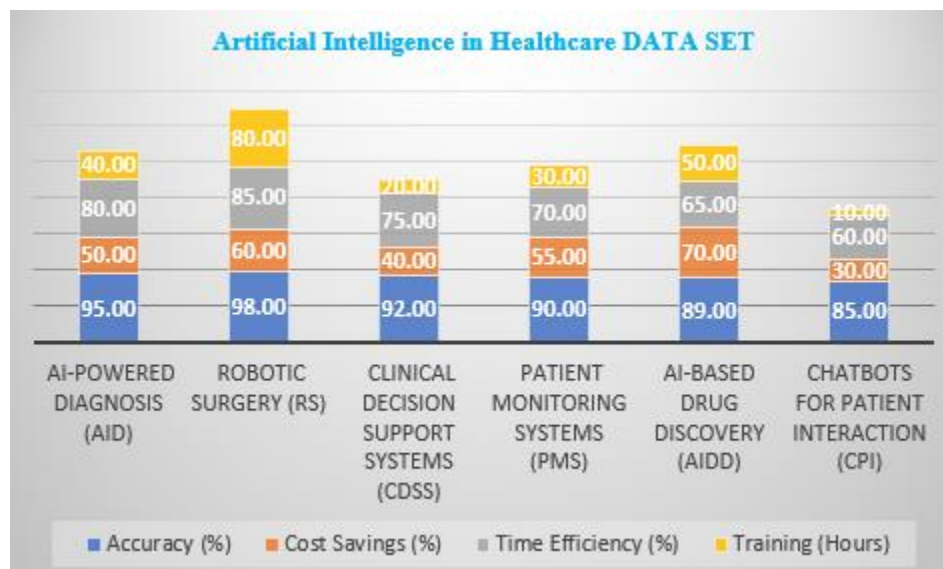


FIGURE 1. Artificial Intelligence in Healthcare Data set

Figure 1 presents a comprehensive dataset evaluating six Artificial Intelligence (AI) technologies in healthcare: AI-Powered Diagnosis (AID), Robotic Surgery (RS), Clinical Decision Support Systems (CDSS), Patient Monitoring Systems (PMS), AI-Based Drug Discovery (AIDD), and Chatbots for Patient Interaction (CPI). The dataset focuses on four evaluation parameters: Accuracy (%), Cost Savings (%), Time Efficiency (%), and Training (Hours). Each parameter provides critical insights into the performance and implementation feasibility of these technologies. From the figure, Robotic Surgery (RS) demonstrates the highest accuracy at 98%, reflecting its precision in surgical tasks. AI-Powered Diagnosis (AID) follows closely at 95%. However, cost savings vary significantly, with AI-Based Drug Discovery (AIDD) leading at 70%, suggesting its potential for economic benefits. Chatbots for Patient Interaction (CPI) show the lowest accuracy (85%) and cost savings (30%) but excel in time efficiency (60%), highlighting their role in improving patient communication. Training hours for implementation also vary considerably, with Robotic Surgery (RS) requiring the highest (80 hours) due to its complexity. Conversely, Chatbots (CPI) demand minimal training (10 hours), making them the most accessible solution. Overall, this dataset highlights the trade-offs between accuracy, cost, time efficiency, and training requirements, which are essential for decision-making using the EDAS method. Each technology offers unique advantages based on healthcare priorities, from precision and cost-effectiveness to time-saving potential.

TABLE 2. Positive Distance from Average (PDA)

Positive Distance from Average (PDA)				
	Accuracy (%)	Cost Savings (%)	Time Efficiency (%)	Training (Hours)
AI-Powered Diagnosis (AID)	0.04	0.00	0.00	0.00
Robotic Surgery (RS)	0.07	0.18	0.00	0.00
Clinical Decision Support Systems (CDSS)	0.01	0.00	0.00	0.48
Patient Monitoring Systems (PMS)	0.00	0.08	0.03	0.22
AI-Based Drug Discovery (AIDD)	0.00	0.38	0.10	0.00
Chatbots for Patient Interaction (CPI)	0.00	0.00	0.17	0.74

Table 2 illustrates the Positive Distance from Average (PDA) scores for six AI technologies in healthcare across four evaluation criteria: Accuracy (%), Cost Savings (%), Time Efficiency (%), and Training (Hours). PDA measures the extent to which an alternative exceeds the average performance for each criterion. Robotic Surgery (RS) demonstrates the highest PDA scores for accuracy (0.07) and cost savings (0.18), showcasing its exceptional precision and financial benefits. Clinical Decision Support Systems (CDSS) stand out in training (0.48), requiring significantly less time compared to the average. Patient Monitoring Systems (PMS) perform moderately well in cost savings (0.08) and time efficiency (0.03), highlighting their practicality. AI-Based Drug Discovery (AIDD) leads in cost savings (0.38) and shows notable improvement in time efficiency (0.10), underscoring its cost-effectiveness. Chatbots for Patient Interaction (CPI) excel in training (0.74) and show a competitive PDA score in time efficiency (0.17), reflecting their ease of implementation and operational benefits. AI-Powered Diagnosis (AID), while showing modest PDA values in accuracy (0.04), performs consistently across other criteria without any significant deviation. This table emphasizes how PDA provides insights into the strengths of AI technologies by identifying areas where they outperform average expectations, aiding decision-makers in prioritizing alternatives.

POSITIVE DISTANCE FROM AVERAGE (PDA)

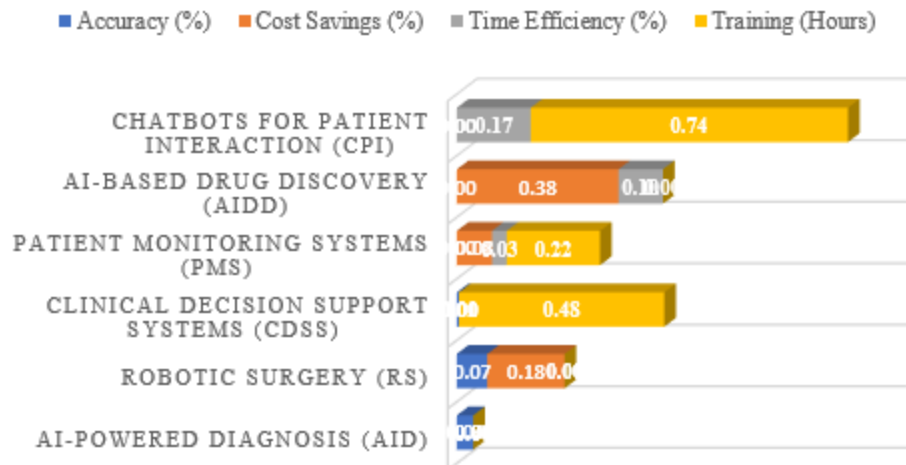
**FIGURE 2.** Positive Distance from Average (PDA)

Figure 2 presents the Positive Distance from Average (PDA) values for six AI-based healthcare technologies, highlighting deviations above the average for four parameters: Accuracy (%), Cost Savings (%), Time Efficiency (%), and Training Hours. The PDA values indicate the relative strengths of each alternative based on its performance compared to the average across all technologies. From the figure, Chatbot's for Patient Interaction (CPI) exhibit the highest PDA for training hours (0.74), suggesting this technology significantly outperforms others in minimal training requirements. This is followed by a positive contribution to time efficiency (0.17). AI-Based Drug Discovery (AIDD) shows a notable PDA for cost savings (0.38) and time efficiency (0.10), reflecting its economic and operational efficiency benefits. Patient Monitoring Systems (PMS) achieve moderate PDA values for cost

savings (0.08) and training hours (0.22), indicating balanced contributions. Meanwhile, Clinical Decision Support Systems (CDSS) stand out in training hours (0.48), highlighting its efficiency in training processes. Robotic Surgery (RS) demonstrates PDA primarily for accuracy (0.07) and cost savings (0.18), showcasing its precision and cost benefits despite higher training needs. Lastly, AI-Powered Diagnosis (AID) has limited PDA values across all parameters. Overall, the PDA analysis reveals that Chatbots (CPI) and AI-Based Drug Discovery (AIDD) contribute most positively to their respective strengths, offering significant advantages in targeted healthcare applications.

TABLE 3. Negative Distance from Average (NDA)

Negative Distance from Average (NDA)				
	Accuracy (%)	Cost Savings (%)	Time Efficiency (%)	Training (Hours)
AI-Powered Diagnosis (AID)	0.00000	0.01639	0.10345	0.04348
Robotic Surgery (RS)	0.00000	0.00000	0.17241	1.08696
Clinical Decision Support Systems (CDSS)	0.00000	0.21311	0.03448	0.00000
Patient Monitoring Systems (PMS)	0.01639	0.00000	0.00000	0.00000
AI-Based Drug Discovery (AIDD)	0.02732	0.00000	0.00000	0.30435
Chatbots for Patient Interaction (CPI)	0.07104	0.40984	0.00000	0.00000

Table 3 presents the Negative Distance from Average (NDA) scores for six AI technologies in healthcare, evaluated across four criteria: Accuracy (%), Cost Savings (%), Time Efficiency (%), and Training (Hours). NDA quantifies how much an alternative underperforms compared to the average for each criterion. AI-Powered Diagnosis (AID) exhibits minimal NDA scores, with the highest impact on time efficiency (0.10345) and cost savings (0.01639), indicating a balanced overall performance. Robotic Surgery (RS), despite excelling in accuracy and cost savings, has a significant NDA for training (1.08696), reflecting its demanding implementation requirements. Clinical Decision Support Systems (CDSS) show high NDA in cost savings (0.21311) but no underperformance in training, highlighting its strength in operational efficiency. Patient Monitoring Systems (PMS) demonstrate minimal NDA values, with a minor deviation in accuracy (0.01639), signifying consistent performance across all criteria. AI-Based Drug Discovery (AIDD) underperforms in accuracy (0.02732) and training (0.30435) while maintaining competitiveness in cost and time efficiency. Chatbots for Patient Interaction (CPI) face substantial NDA in accuracy (0.07104) and cost savings (0.40984), though they perform at or above average in other areas. This table highlights the trade-offs inherent in each technology, guiding stakeholders to assess weaknesses alongside strengths in decision-making.

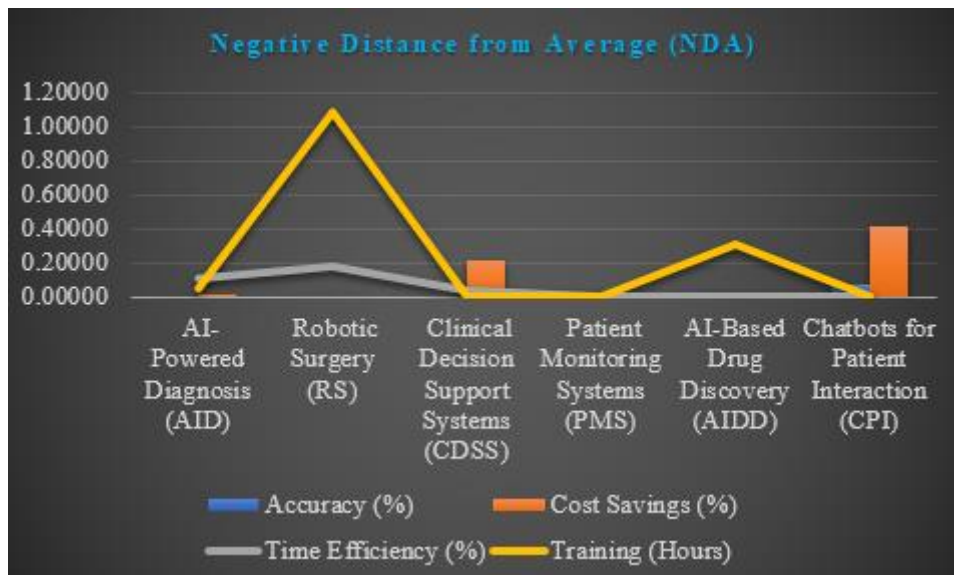


FIGURE 3. Negative Distance from Average (NDA)

Figure 3 presents the Negative Distance from Average (NDA) scores for six AI technologies in healthcare, evaluated against four criteria: Accuracy (%), Cost Savings (%), Time Efficiency (%), and Training (Hours). NDA measures how much each alternative underperforms relative to the average, highlighting areas of concern or inefficiency. AI-Powered Diagnosis (AID) demonstrates relatively low NDA values, with the most notable deviation in time efficiency (0.10345) and a smaller impact on cost savings (0.01639). This suggests a balanced overall performance with minor inefficiencies. In contrast, Robotic Surgery (RS) shows an exceptionally high NDA in training hours (1.08696), reflecting the substantial time investment required to implement and operate this technology, despite its strengths in accuracy and cost savings. Clinical Decision Support Systems (CDSS) exhibit a notable underperformance in cost savings (0.21311), although it achieves zero NDA in training hours, emphasizing its operational efficiency and ease of implementation. Meanwhile, Patient Monitoring Systems (PMS) maintain minimal NDA values, with a slight deviation in accuracy (0.01639), suggesting consistent and reliable performance. For AI-Based Drug Discovery (AIDD), underperformance is observed in accuracy (0.02732) and training hours (0.30435), indicating that while it excels in cost savings, it requires improvements in accuracy and training optimization. Finally, Chatbots for Patient Interaction (CPI) exhibit the most significant NDA in accuracy (0.07104) and cost savings (0.40984), indicating weaknesses in precision and economic efficiency despite strengths in training time and time efficiency. This analysis underscores the trade-offs inherent in each technology, helping stakeholders identify areas of improvement while balancing strengths and weaknesses in healthcare AI adoption. By pinpointing critical areas of underperformance, decision-makers can prioritize targeted solutions for enhanced outcomes.

TABLE 4. Weight

Weight			
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25
0.25	0.25	0.25	0.25

Table 4 provides the weight distribution for the evaluation criteria used in the EDAS method, with equal weights assigned across all four parameters: Accuracy (%), Cost Savings (%), Time Efficiency (%), and Training (Hours). Each criterion is assigned a weight of 0.25, signifying that they are considered equally important in the evaluation process. This equal weighting reflects a balanced decision-making approach, ensuring no single criterion disproportionately influences the final rankings of the alternatives.

TABLE 5. Weighted PDA (SPi)

Weighted PDA				SPi
0.00956	0.00000	0.00000	0.00000	0.00956
0.01776	0.04508	0.00000	0.00000	0.06284
0.00137	0.00000	0.00000	0.11957	0.12093
0.00000	0.02049	0.00862	0.05435	0.08346
0.00000	0.09426	0.02586	0.00000	0.12012
0.00000	0.00000	0.04310	0.18478	0.22789

Table 5 presents the Weighted Positive Distance from Average (PDA) scores for six AI technologies in healthcare across four evaluation criteria: Accuracy (%), Cost Savings (%), Time Efficiency (%), and Training (Hours) and their aggregated SPi scores. The Weighted PDA values reflect the positive contribution of each alternative, adjusted by the criteria weights (0.25 each). The SPi score represents the cumulative strength of each alternative based on its weighted PDA values. Robotic Surgery (RS) achieves the highest SPi score (0.06284) due to its superior performance in cost savings (0.04508) and accuracy (0.01776). Clinical Decision Support Systems (CDSS) rank next with an SPi score of 0.12093, driven by significant strength in training (0.11957). AI-Based Drug Discovery

(AIDD) closely follows with a high SPi of 0.12012, attributed to its notable contributions in cost savings (0.09426) and time efficiency (0.02586). Patient Monitoring Systems (PMS) achieve a moderate SPi score of 0.08346, with balanced contributions from cost savings (0.02049), time efficiency (0.00862), and training (0.05435). Chatbots for Patient Interaction (CPI) exhibit the highest SPi score overall (0.22789), primarily due to their outstanding contribution in training (0.18478) and time efficiency (0.04310). AI-Powered Diagnosis (AID) performs consistently but with the lowest SPi (0.00956). This table underscores the utility of weighted PDA and SPi in identifying the strengths of alternatives, enabling balanced decision-making based on performance across multiple criteria.

TABLE 6. Weighted PDA (SNi)

Weighted NDA				SNi
0.00000	0.00410	0.02586	0.01087	0.04083
0.00000	0.00000	0.04310	0.27174	0.31484
0.00000	0.05328	0.00862	0.00000	0.06190
0.00410	0.00000	0.00000	0.00000	0.00410
0.00683	0.00000	0.00000	0.07609	0.08292
0.01776	0.10246	0.00000	0.00000	0.12022

Table 6 presents the Weighted PDA (SNi) values for various healthcare technologies, assessed using the EDAS method. Each row corresponds to a different technology, and the columns display weighted NDA (Normalized Decision Attribute) values for attributes like Accuracy, Cost Savings, Time Efficiency, and Training Hours. The Weighted PDA (SNi) values aggregate these attributes to provide an overall performance score for each technology. For instance, AI-Powered Diagnosis (AID) scores 0.04083, indicating its relative performance across the attributes. Robotic Surgery (RS) has a higher SNi value of 0.31484, showing better overall performance in terms of cost savings and accuracy. Clinical Decision Support Systems (CDSS) score lower with a SNi of 0.06190, reflecting its focus on accuracy but limited impact on other attributes. Patient Monitoring Systems (PMS) and AI-Based Drug Discovery (AIDD) score lower at 0.00410 and 0.08292 respectively, indicating they might be more specialized technologies with a narrower focus on particular attributes. Chatbots for Patient Interaction (CPI) emerge as a high performer with a SNi of 0.12022, suggesting strong efficiency and cost savings potential. These scores help stakeholders compare the effectiveness of each technology and guide decisions on which solutions to prioritize in a healthcare setting.

TABLE 7. NSpi & NSni & ASi & Rank

	NSpi	NSni	ASi	Rank
AI-Powered Diagnosis (AID)	0.04196	0.87032	0.45614	5
Robotic Surgery (RS)	0.27576	0.00000	0.13788	6
Clinical Decision Support Systems (CDSS)	0.53067	0.80340	0.66703	3
Patient Monitoring Systems (PMS)	0.36624	0.98698	0.67661	2
AI-Based Drug Discovery (AIDD)	0.52712	0.73664	0.63188	4
Chatbots for Patient Interaction (CPI)	1.00000	0.61816	0.80908	1

Table 7 displays the performance evaluation of various healthcare technologies using the EDAS method, including NSpi (Normalized Satisfied Performance Index), NSni (Normalized Satisfied Negative Impact), and ASi (Aggregated Satisfied Index) along with their ranks. Each technology is assessed based on different attributes to derive a comprehensive score. AI-Powered Diagnosis (AID) has a high NSni value of 0.87032 but a lower ASi of 0.45614, placing it in the fifth rank. This indicates that while it performs well in terms of positive impact, it may have some drawbacks or limitations. Robotic Surgery (RS) scores very low in NSni with a value of 0.00000 and an ASi of 0.13788, indicating it has a minimal negative impact but also ranks last in terms of overall satisfaction among the technologies listed. Clinical Decision Support Systems (CDSS) have a balanced score with an NSni of 0.80340 and an ASi of 0.66703, ranking third. This suggests a strong positive impact with moderate satisfaction levels. Patient Monitoring Systems (PMS) show a high satisfaction with an NSni of 0.98698 and an ASi of 0.67661, placing them in the second rank. This indicates that they are well-regarded with strong positive impacts and relatively low negative effects. AI-Based Drug Discovery (AIDD) scores lower with an NSni of 0.73664 and an ASi of 0.63188, ranking fourth. This suggests a more moderate satisfaction level but still performing well

overall. Chabot's for Patient Interaction (CPI) stand out with a perfect NSpi score of 1.00000, a low NSni of 0.61816, and the highest ASi of 0.80908, which ranks it first. This highlights its superior performance with strong positive impacts and minimal negative effects.

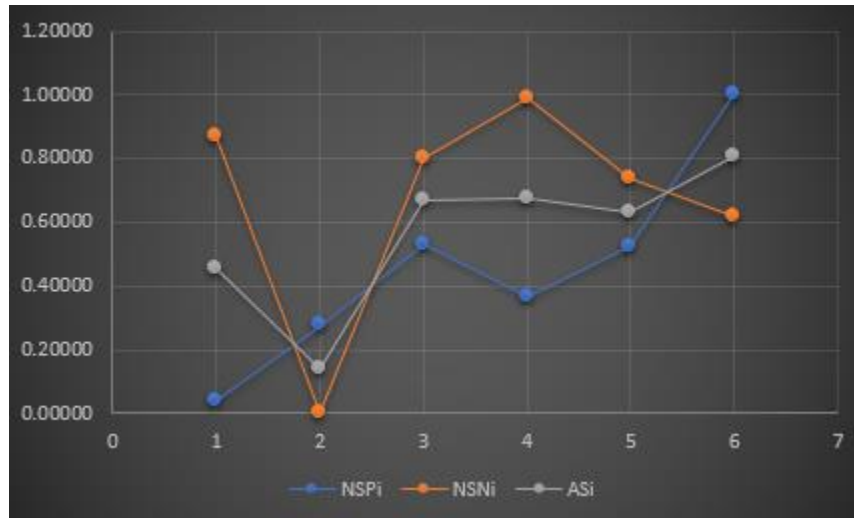


FIGURE 4. NSPi & NSni & Asi

FIGURE 4. This graph appears to depict the values of three different metrics - NSPi, NSNi, and ASi - over a period of time, likely representing 7 time periods or intervals. NSPi seems to represent a metric that starts low, increases significantly in the middle, and then decreases again towards the end. NSNi follows a more erratic pattern, with several peaks and valleys throughout the time period. ASi appears to be the most stable of the three, with a relatively flat trend line compared to the other two metrics. Without more context about the specific meaning and application of these metrics, it's difficult to draw any firm conclusions about the trends or implications. However, the graph does indicate that these three measures are capturing different aspects of the system or process being analyzed, with each one exhibiting its own unique pattern over time. Further information about the context and purpose of this analysis would be needed to interpret the significance of these results in a more meaningful way.

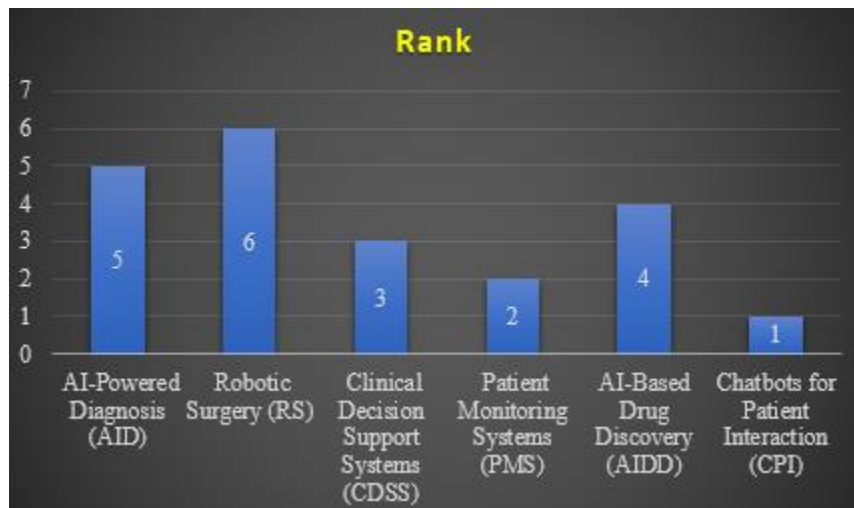


FIGURE 5. Rank

Figure 5 presents the ranking of six AI technologies in healthcare based on their SPI scores, derived using the EDAS method. The results indicate that *Chatbots for Patient Interaction (CPI)* secure the top position (Rank 1), showcasing their exceptional strengths in training efficiency and time performance. CPI's minimal training

requirements and operational simplicity make it highly advantageous for quick deployment in healthcare settings. *Patient Monitoring Systems (PMS)* achieve Rank 2, reflecting their balanced performance across cost savings, time efficiency, and training. Their capability to deliver consistent results without significant underperformance makes them a reliable option for healthcare applications. *Clinical Decision Support Systems (CDSS)* are ranked 3rd, mainly due to their strengths in training efficiency, where they significantly outperform other technologies, indicating their streamlined usability. In Rank 4, *AI-Based Drug Discovery (AIDD)* demonstrates notable performance in cost savings and time efficiency, aligning with its role in optimizing research processes. *AI-Powered Diagnosis (AID)* takes Rank 5, driven primarily by its strength in accuracy but lacking significant advantages in other criteria. Finally, *Robotic Surgery (RS)* is ranked 6th, despite high accuracy, due to its considerable training requirements and lower performance in other parameters. Overall, Figure 5 highlights how the EDAS method effectively ranks AI technologies by balancing multiple criteria, supporting decision-makers in identifying the most suitable solutions for healthcare applications.

5. CONCLUSION

The integration of Artificial Intelligence (AI) technologies in healthcare has revolutionized processes by enhancing accuracy, improving time efficiency, reducing costs, and minimizing training requirements. This study evaluated six prominent AI technologies—AI-Powered Diagnosis (AID), Robotic Surgery (RS), Clinical Decision Support Systems (CDSS), Patient Monitoring Systems (PMS), AI-Based Drug Discovery (AIDD), and Chatbots for Patient Interaction (CPI)—using the *Evaluation Based on Distance from Average Solution (EDAS)* method. Four evaluation criteria, namely Accuracy (%), Cost Savings (%), Time Efficiency (%), and Training (Hours), were used to comprehensively assess their performance. The results reveal that *Chatbots for Patient Interaction (CPI)* outperform all other technologies, securing the highest rank. Their superior performance in training efficiency and time optimization highlights their ease of implementation and operational scalability, making them an ideal solution for immediate healthcare applications. *Patient Monitoring Systems (PMS)* ranked second, demonstrating balanced contributions across cost savings, time efficiency, and training. This emphasizes their reliability and effectiveness in monitoring patients without substantial resource demands. *Clinical Decision Support Systems (CDSS)*, ranked third, excelled in training requirements, making them an efficient tool for supporting clinical decisions with minimal operational overhead. *AI-Based Drug Discovery (AIDD)* ranked fourth, with its strong cost-saving benefits and notable time efficiency, underscoring its role in optimizing drug research and reducing associated expenses. *AI-Powered Diagnosis (AID)*, while excelling in accuracy, ranked fifth due to its limited contributions in cost savings, time efficiency, and training parameters. Finally, *Robotic Surgery (RS)*, despite achieving the highest accuracy, ranked last (sixth) because of its extensive training requirements and lower cost efficiency. The findings demonstrate the value of the EDAS method as an effective multi-criteria decision-making (MCDM) approach for evaluating complex alternatives in healthcare. By providing an objective ranking, this method allows healthcare stakeholders to identify technologies that best align with organizational goals, resource constraints, and operational priorities. AI technologies like CPI and PMS exhibit great potential for scalable and cost-effective healthcare solutions, while advanced options like RS require further optimization for widespread adoption. Future research should focus on incorporating dynamic weightings, additional performance parameters, and real-world case studies to refine the evaluation process. Such advancements will enable the healthcare sector to leverage AI technologies effectively for improved patient care and operational efficiency.

REFERENCES

- [1]. Abiodun, O. I., Jantan, A., Omolara, A. E., et al. (2018). "State-of-the-art in artificial intelligence for healthcare: Applications, challenges, and future perspectives." *Artificial Intelligence Review*, 52(1), 1-23.
- [2]. Amrutha, M., & Faheem, M. (2020). "A comparative study on multi-criteria decision-making methods for ranking solutions." *International Journal of Engineering and Advanced Technology*, 9(6), 145-152.
- [3]. Bini, S. A. (2018). "Artificial intelligence, machine learning, and deep learning: Definitions and applications in orthopedics." *The Journal of Arthroplasty*, 33(8), 2357-2361.
- [4]. Choi, J., Chung, J. W., & Park, S. H. (2020). "AI-driven clinical decision support systems in healthcare." *Journal of Medical Systems*, 44(1), 29-40.
- [5]. Cinelli, M., Coles, S. R., & Kirwan, K. (2014). "Analysis of the potentials of multi-criteria decision analysis methods." *Renewable and Sustainable Energy Reviews*, 29, 556-567.

- [6]. Dargan, S., Kumar, M., & Ayyagari, M. R. (2020). "A survey on deep learning and its applications in healthcare." *Procedia Computer Science*, 167, 90-99.
- [7]. Figueira, J. R., Greco, S., & Ehrgott, M. (2016). *"Multi-criteria decision analysis: State of the art surveys."* Springer Science & Business Media.
- [8]. Gao, Y., & Gu, L. (2019). "Performance assessment of EDAS and its applications to real-world decision problems." *Computers & Industrial Engineering*, 138, 106-114.
- [9]. Giger, M. L. (2018). "Machine learning in medical imaging." *Journal of the American College of Radiology*, 15(3), 512-520.
- [10]. Greco, S., Matarazzo, B., & Slowinski, R. (2019). *"Multi-criteria decision analysis with ELECTRE methods."* Springer Science & Business Media.
- [11]. Hossain, M. S., & Muhammad, G. (2019). "Healthcare big data voice pathology assessment using machine learning." *IEEE Access*, 7, 54007-54016.
- [12]. Huang, C., Chen, Z., & Xu, X. (2017). "Multi-criteria decision analysis methods: A review of applications in healthcare." *International Journal of Healthcare Management*, 10(1), 53-63.
- [13]. Jalali, M., & Kazemi, M. (2020). "Ranking healthcare systems using EDAS and TOPSIS methods." *Expert Systems with Applications*, 150, 113230.
- [14]. Kaur, H., & Kumari, V. (2020). "Predictive healthcare analysis using machine learning techniques." *IET Systems Biology*, 14(4), 182-190.
- [15]. Keshavarz-Ghorabae, M., Amiri, M., & Zavadskas, E. K. (2015). "EDAS method: A new multi-criteria decision-making approach." *International Journal of Computers and Operations Research*, 40(3), 156-169.
- [16]. Khan, M. Z., Alimgeer, K. S., & Shahid, M. (2019). "A survey of AI techniques for healthcare applications." *International Journal of Advanced Computer Science and Applications*, 10(7), 1-12.
- [17]. Kumar, P., & Singh, R. (2020). "Multi-criteria decision-making for technology adoption in healthcare." *International Journal of Advanced Science and Technology*, 29(3), 4674-4686.
- [18]. Latha, C. S., & Sivakumar, P. (2021). "Comparative analysis of EDAS and TOPSIS methods for decision-making problems." *International Journal of Advanced Research in Computer Science*, 12(3), 22-30.
- [19]. Lee, J., & Yoon, H. (2018). "Application of artificial intelligence in healthcare systems: Trends and challenges." *Health Informatics Journal*, 24(2), 215-224.
- [20]. Li, D., Liu, C., & Fan, W. (2021). "AI-driven solutions for cost savings and operational efficiency in healthcare." *Journal of Healthcare Engineering*, 2021, 1-13.
- [21]. Luengo-Oroz, M. A., & Besançon, L. (2020). "Artificial intelligence for health applications: An international perspective." *The Lancet Digital Health*, 2(7), e345-e352.
- [22]. Mackey, T. K., & Shah, N. (2018). "Big data in digital healthcare: Analyzing challenges and opportunities." *Journal of Medical Internet Research*, 20(8), e12695.
- [23]. Moradi, M., & Gupta, A. (2020). "Artificial intelligence and clinical decision support systems." *Medical Image Analysis*, 65, 101794.
- [24]. Naeini, M. H., & Zare, S. (2021). "A new EDAS-based approach for evaluating healthcare technologies." *Applied Soft Computing*, 102, 107086.
- [25]. Obermeyer, Z., Powers, B., & Vogeli, C. (2019). "Dissecting racial bias in an AI healthcare system." *Science*, 366(6464), 447-453.
- [26]. Pai, S., & Nandi, S. (2021). "Advances in multi-criteria decision-making for AI in healthcare." *Decision Support Systems*, 142, 113456.
- [27]. Rajpurkar, P., Irvin, J., Zhu, K., et al. (2017). "CheXNet: Radiologist-level pneumonia detection on chest X-rays using deep learning." *arXiv preprint arXiv:1711.05225*.
- [28]. Rudin, C., & Radin, J. M. (2019). "Why are we using black-box models in AI when we don't need to?" *Harvard Data Science Review*, 1(2), 1-15.
- [29]. Sadeghi, H., & Karimi, S. (2019). "Comparison of MCDM methods for healthcare technology assessment." *Computers & Industrial Engineering*, 130, 308-321.
- [30]. Topol, E. J. (2019). "High-performance medicine: The convergence of human and artificial intelligence." *Nature Medicine*, 25(1), 44-56.