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Artificial Intelligence in Health Economics and Outcomes Research (HEOR): Advancing Cost-Effectiveness Analysis, Reimbursement Decision-Making, and Healthcare Policy

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ABSTRACT

Background: The application of artificial intelligence (AI) to health economics and outcomes research (HEOR) will change the game in how large, heterogeneous, real-world healthcare datasets can be analyzed.

Purpose: To provide an overview of AI in HEOR, with an emphasis on predictive analytics, real-world evidence creation, cost-effectiveness modelling, and clinical decision support.

Methods: A narrative review approach was used to summarize existing evidence about the use of machine learning (ML), natural language processing (NLP), and deep learning (DL) techniques in the context of HEOR.

Results: AI-driven approaches facilitate higher-quality data analysis, a faster research process, and increased accuracy in predicting health-related and economic outcomes. ML models predict clinical outcomes based on electronic medical records, whereas NLP provides for the interpretation of clinical findings from free-text notes. These technologies are directly related to cost-effectiveness analysis and reimbursement policies.

Conclusion: Although AI has many benefits in terms of its impact on HEOR research, there are still some unresolved issues, such as data security issues, biases in AI algorithms, and the lack of regulatory frameworks.

1. Introduction

Artificial Intelligence (AI) is a broad term used to refer to a chain of technologies, i.e., machine learning, natural language processing, and predictive analytics, which empower computers to undertake tasks that would otherwise necessitate human intelligence (Paramesha *et al.*, 2024). AI has changed almost every industry, including healthcare. In fact, there are numerous ways AI can be used in medicine; for example, it can help with medical imaging, making diagnoses, personalizing treatment plans, and identifying new drugs (Eskandar, 2023). AI solutions in healthcare will increase productivity, reduce mistakes by humans, and improve patient outcomes through faster and more efficient analysis of large amounts of healthcare data than ever before. AI also makes administrative tasks easier with workflow automation, documentation automation, and optimization of resources. The most promising application of AI in healthcare is its application in Health Economics and Outcomes Research (HEOR) (Dasari *et al.*, 2024).

HEOR is a multi-professional science that quantifies the economic and clinical value of healthcare interventions. HEOR creates useful information for stakeholders like healthcare clinicians, policymakers, and pharmaceutical companies to confirm that treatments and medical technology are delivering maximum value at minimum costs. AI greatly enhances HEOR by allowing more accurate and data-driven analysis, enhancing the performance of economic modeling, and making it easier to build real-world evidence (Shiwlani *et al.*, 2024). Conventional HEOR methods have historically depended on formal sources of information like clinical trial outcomes and patient questionnaires (Hawasli, 2024). AI, however, can harvest and analyze unstructured, large volumes of data from social media, genomics, wearable technology, and electronic health records. By applying machine learning algorithms, AI detects correlations and patterns potentially not detectable by traditional statistical models (Boni *et al.*, 2024).

Predictive modeling and simulations based on AI enable researchers to predict treatment outcomes in patients and policymakers to determine the most vital treatments for money (Onyango *et al.*, 2022). Another important use of AI in HEOR is that it can produce real-world evidence (RWE). Clinical trials have long been considered the gold standard for measuring the strength of treatments, but they are expensive, time-consuming, and not very generalizable. AI can retrieve RWD from more than one source by harvesting insurance claims, hospital discharge data, as well as patient self-reported outcomes, to establish data about real-world performance from treatment. AI applications can speed up literature reviews, summarize large scientific data, and produce evidence synthesis reports considerably more efficiently than manual means (Wagner *et al.*, 2022).

This hastens the approval process of novel treatments and enables healthcare systems to make well-informed and timely reimbursement decisions. While it is associated with many advantages, the use of AI in HEOR has challenges. Compliance with laws like the General Data Protection Regulation (GDPR) and the Health Insurance Portability and Accountability Act (HIPAA) is important to allay patients' fears (Isibor, 2024; Subramanian *et al.*, 2024). The quality of input data also has an impact on the accuracy of AI models. Biased training data can lead to biased results, which may impact certain patient groups disproportionately. Only consistent monitoring and moral oversight of AI uses in HEOR can make this credibility and fairness guarantee. Typically, AI is revolutionizing Health Economics and Outcomes Research by assisting in data analysis, predictive modeling, and the creation of real-world evidence. Through its capacity to process healthcare data at scale, it provides more precise cost-effectiveness estimates, enables evidence-based decision-making, and automates health technology assessments. However, effective application of AI in HEOR will have to address challenges of data privacy, bias, and regulation (Chirikov & Kroep, 2024).

With advancing technology, its application in HEOR will be the determining factor in shaping healthcare's future, rendering medical treatment clinically effective and available (Alowais *et al.*, 2023). This review article critically evaluates the current and potential uses of AI in HEOR, its benefits, limitations, and promises, with the aim of directing researchers, clinicians, and policymakers on how to use AI in improving healthcare decision-making and outcomes. To contextualize these applications, the following sections briefly outline the foundational concepts of HEOR methodology and key AI technologies.

2. Understanding Health Economics and Outcomes Research

2.1. Definition and Scope of HEOR

Health Economics and Outcomes Research (HEOR) is a multidisciplinary science comparing the economic, clinical, and humanistic effects of healthcare interventions (Dang, 2025). HEOR is an essential component of healthcare decision-making, as it offers estimates of the value of medical interventions, technologies, and services. HEOR offers beneficial information concerning the distribution of healthcare resources such that the medical interventions deliver maximum benefits for a reasonable cost. It acts as a link between healthcare policy and clinical research to enable evidence-based decision-making by pharmaceutical companies, payers, governments, healthcare providers, and other stakeholders (Dang, 2025). HEOR applications cut across a wide spectrum of areas of healthcare evaluation, such as cost-effectiveness analysis, HTA, patient-reported outcomes, and real-world evidence development. HEOR enables the integration of clinical research and economic theory to translate the worth of medical interventions into dollar values larger than clinical effectiveness. This is useful if health spending increases and stakeholders want to optimize resource consumption and deliver enhanced patient benefits (Figure 1).

HEOR has two principal focus areas: health economics and outcomes research. Health economics deals with the cost effect of healthcare interventions, direct costs (treatment cost, hospitalization), and indirect costs (loss of productivity, caregiver time) (Abraham *et al.*, 2024). It employs several economic models, such as cost-effectiveness analysis (CEA), cost-utility analysis (CUA), and budget impact analysis (BIA), to measure the value of investing in healthcare quantitatively. Outcomes research, nonetheless, establishes the clinical and humanistic impacts of healthcare interventions, measuring patient-oriented outcomes such as quality of life, treatment adherence, and disease burden. HEOR, through the convergence of these two types of knowledge, makes an evidence-based evaluation of healthcare interventions, whereby they are not just clinically effective but also economically viable (Hawasli, 2024).

2.2. Traditional Methods in HEOR

HEOR has historically relied on a variety of methods to evaluate healthcare interventions. They are both quantitative and qualitative in nature to measure economic and health outcomes. Some of the most common traditional methods in HEOR are clinical trials, economic modeling, real-world evidence studies, and patient-reported outcomes measures.

2.2.1. Clinical Trials and Randomized Controlled Trials (RCTs)

Randomized Controlled Trials (RCTs) have long been considered the gold standard in the evaluation of the safety and efficacy of medical interventions. RCTs involve randomizing patients to intervention groups with the objective of minimizing bias and obtaining strong comparisons between interventions. RCTs yield high-quality evidence on treatment effect, side effects, and patient outcomes in controlled settings. In spite of the valuable information that RCTs offer, there are some limitations. They are usually expensive, time-consuming, and limited in their generalizability because they might not be applicable to typical patient populations in clinical practice (Serrano-Ripoll *et al*., 2022). RCTs will typically exclude patients with high numbers of comorbidities or non-adherent patients with respect to the treatment protocols very strictly, and it will be difficult to understand how the interventions operate under typical clinical practice. Despite these limitations, RCTs are an integral component of HEOR and provide valuable baseline information to inform future economic and outcomes evaluation.

2.2.2. Cost-Effectiveness Analysis (CEA) and Cost-Utility Analysis (CUA)

Cost-effectiveness analysis (CEA) is a component of health economic evaluation. It is constituted by the synthesis of cost and health outcomes across different interventions to identify which intervention represents the best value for money. CEA is generally defined as the cost per unit of health benefit, i.e., cost per decrease in disease severity or cost per life-year gained. It helps policymakers and clinicians decide where to spend limited healthcare budgets. More precise within CEA is cost-utility analysis (CUA), applying quality-adjusted life years (QALYs) or disability-adjusted life years (DALYs) as indices in measuring the quality and quantity of life an intervention provides. By assigning a utility value to different states of health, CUA has a more patient-centered assessment of gains via treatment (Brent, 2023). Some healthcare systems, such as the UK's National Institute for Health and Care Excellence (NICE), use CUA thresholds to make funding decisions on new treatments.

2.2.3. Budget Impact Analysis (BIA)

Budget Impact Analysis (BIA) takes into consideration the cost implications at the point when a new healthcare intervention becomes implemented in some healthcare system or payer environment. Compared to CEA's focus on cost-effectiveness, BIA captures the entirety of the affordability of an intervention by estimating its impact on healthcare budgets. It considers treatment take-up, the patient group, as well as future expenses (Chugh *et al*., 2021). BIA is best designed for application by insurers and policymakers to estimate the economic viability of new treatment launches.

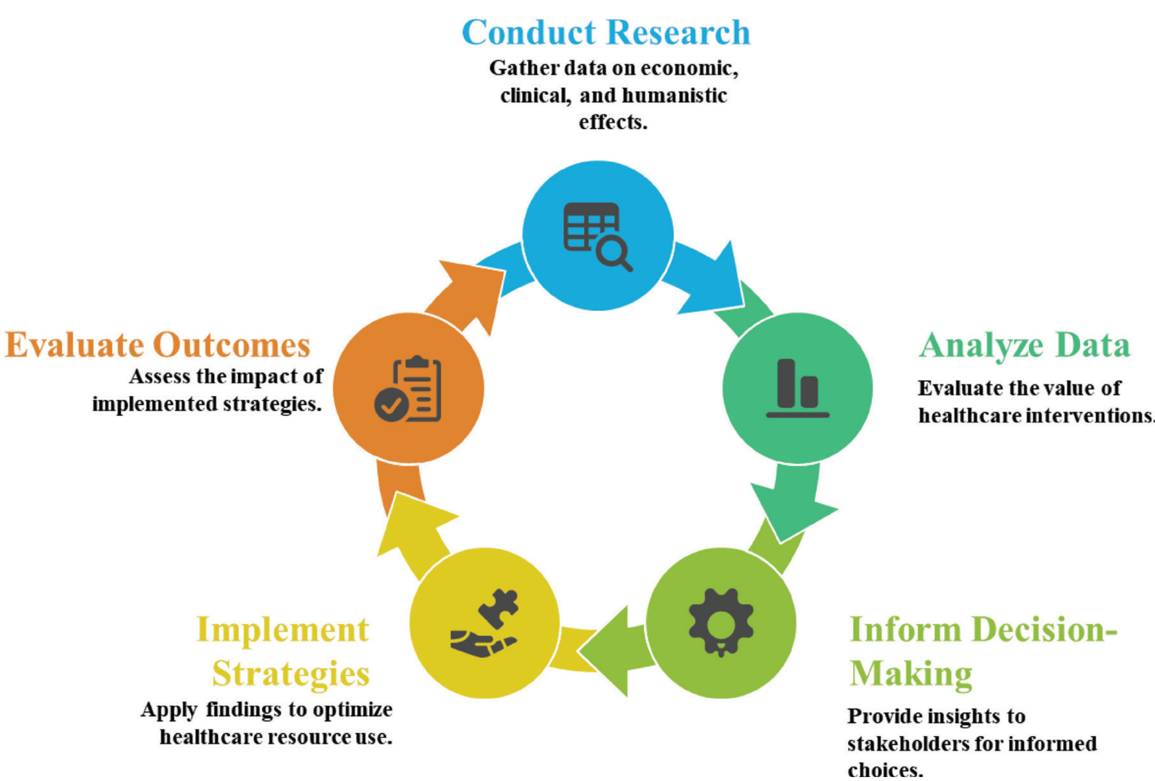

Figure 1: Health Economic and Outcome Research Process

2.2.4. Real-World Evidence (RWE) and Observational Studies

Real-world evidence (RWE) has emerged as having a prominent role in HEOR as a supplement to clinical trial evidence. RWE is constructed from real-world data (RWD), including electronic health records (EHRs), claims, disease registries, and patient-reported outcomes. Observational studies, including cohort studies and case-control studies, analyze these sources of data to compare the effectiveness, safety, and healthcare utilization of treatments under real-world settings. Relative to RCTs, conducted under controlled environments, RWE studies capture the imperfections of actual healthcare environments, monitoring treatment adherence, long-term outcomes, and healthcare resource utilization (Dang, 2025). Thus, RWE is especially important for post-market surveillance, pharmacovigilance, and comparative effectiveness studies. Nevertheless, RWE studies are challenged by data quality issues, possible biases, and requirements for advanced statistical analyses to overcome confounding factors.

2.2.5. Health Technology Assessment (HTA)

Health Technology Assessment (HTA) is a systematic analysis of medical technology such as drugs, devices, procedures, and health services. HTA takes into account clinical effectiveness, safety, cost-effectiveness, and ethics in informing policy for healthcare and reimbursement. HTA combines a variety of HEOR methodologies, such as clinical trial data, economic modeling, and real-world evidence, to gain an overview of new medical technologies. Nearly all nations have established HTA agencies like the UK's National Institute for Health and Care Excellence (NICE), Canada's Agency for Drugs and Technologies in Health (CADTH), and the US's Institute for Clinical and Economic Review (ICER) (Zisis *et al*., 2024). These agencies apply HEOR principles to decide on healthcare funding in a way that new technologies are substantial in their health effect relative to cost.

2.2.6. Patient-Reported Outcomes (PROs) and Quality of Life Assays

Patient-reported outcomes (PROs) are equally important in HEOR because PROs are the patient's own interpretation of his illness, symptoms, and treatment process. PROs give insights on the treatment benefits, including the clinical outcome, emphasizing decreased pain, regain of function, and mental status. Quality-of-life questionnaires like the EQ-5D and SF-36 are utilized predominantly in HEOR to capture the health-related quality of life (HRQoL). The measurements constitute a core part of cost-utility analyses, and they are useful in determining the effect of interventions on patients' health (Campbell *et al*., 2021). PROs find specific application in chronic diseases, where symptom management and patient satisfaction over the long term are key concerns (Table 1).

Table: 1 Comparative Table of Traditional Health Economics and Outcomes Research (HEOR)

Method	**Purpose**	**Data Source**	**Strengths**	**Limitations**
Randomized Controlled Trials (RCTs)	Evaluate efficacy and safety of interventions	Controlled experimental data	High internal validity, minimized bias	Expensive, time-consuming, limited generalizability
Cost-Effectiveness Analysis (CEA)	Compare costs and health outcomes of interventions	Clinical trials, models	Helps identify best-value treatments	Doesn't capture quality of life
Cost-Utility Analysis (CUA)	Evaluate value using QALYs or DALYs	Clinical trials, PROs, models	Includes quality and quantity of life in analysis	Utility values can be subjective and population-dependent
Budget Impact Analysis (BIA)	Estimate affordability of new interventions	Epidemiological data, market uptake, cost data	Useful for short-term financial planning by payers	Ignores long-term clinical outcomes
Real-World Evidence (RWE)	Assess treatment performance in actual practice	EHRs, claims data, registries	Reflects real clinical settings, captures broader population	Prone to confounding, bias, and inconsistent data quality
Health Technology Assessment (HTA)	Inform reimbursement and policy decisions	Synthesized evidence from multiple methods	Multidimensional analysis: clinical, economic, ethical	Complex process, dependent on national policies
Patient-Reported Outcomes (PROs)	Capture patients' perspectives on health status	Surveys, questionnaires (e.g., EQ-5D, SF-36)	Reflects patient-centred care and QoL impacts	Subjective reporting, may lack consistency across populations

3. AI Technologies in Healthcare

3.1. Types of AI Technologies Used

Having established the HEOR framework above, this section introduces the AI methodologies that are now being applied with it. Artificial Intelligence (AI) has transformed healthcare through increased analysis of information, improved diagnostic ability, improved treatment planning, and streamlined administrative processes. AI refers to a collection of technologies that enable machines to perform intellectual functions traditionally the domain of human intellect, such as reasoning, learning, and decision-making. There are different forms of AI technologies in healthcare, each with different abilities responsible for increased patient care and the performance of the health system.

3.1.1. Machine Learning (ML)

Machine Learning (ML) is one of the Artificial Intelligence subdomains that works on the process of training algorithms to predict and identify patterns in large datasets. ML models have certain uses in medicine for disease prediction, risk assessment, and personalized treatment. The algorithms are trained on patient historical data to arrive at correlations between symptoms, gene-level predispositions, and disease progression (Albahra *et al.*, 2023). ML methods include supervised learning, where the models are trained using labeled data, and unsupervised learning, where they find hidden patterns without labels. Another ML method being used more and more is reinforcement learning.

3.1.2. Deep Learning (DL)

Deep Learning (DL), which is the most recent version of ML, uses neural networks to analyze large amounts of medical data. Deep learning approaches, such as CNN and RNN, have been applied extensively in the fields of medical imaging, speech recognition, and NLP (Yadav *et al.*, 2022). CNNs are widely used in radiology and pathology for detecting abnormalities in X-ray, MRI, and CT scans, whereas RNNs assist in processing sequence-based medical data such as patient history and DNA sequences.

3.1.3. Natural Language Processing (NLP)

Natural Language Processing (NLP) is an area that allows computer systems to interpret human languages by reading and generating them. This technology finds application in healthcare informatics when using electronic health records (EHR) to extract meaningful data from clinical notes (Thatoi *et al.*, 2023). Chat-bots and virtual assistants based on NLP enhance patient engagement by screening for symptoms, answering health questions, and offering mental health assistance. NLP also helps in literature review by condensing medical research and establishing future directions in disease management.

3.1.4. Robotic Process Automation (RPA)

Robotic Process Automation (RPA) automates repetitive administrative tasks in healthcare, such as appointment management, insurance claims processing, and patient information management. RPA increases business efficiency by reducing human errors, paperwork, and workflow process optimization. Healthcare providers spend less time on administrative tasks and more on actual patient care with AI-driven automation integrated into the system (Nimkar *et al.*, 2024).

3.1.5. Computer Vision

Computer vision, the field of artificial intelligence that offers computer vision capability so that computers can read and interpret visual data, is widely applied in dermatology, medical imaging, pathology, and ophthalmology. Computer vision systems based on artificial intelligence identify radiographic pathology such as cardiovascular diseases, tumors, and fractures at high sensitivity levels. AI applications in dermatology screen for moles and skin lesions and subsequently identify precancerous markers for melanoma (Patel *et al.*, 2023). In ophthalmology, AI applications identify glaucoma and diabetic retinopathy.

3.1.6. Predictive Analytics and Big Data

Predictive analytics leverages the use of artificial intelligence and big data techniques to forecast disease outbreaks, optimize hospital resource planning, and improve patient outcomes. By examining large datasets, from demographic data and genomic data to lifestyle measurement, predictive models flag patients at risk and suggest early intervention programs (Kosaraju, 2024). Predictive analytics also accelerates drug development by pharma companies by predicting compound efficacy and quantifying potential side effects (Figure 2).

3.2. Applications of AI in Diagnosis and Treatment

AI has revolutionized disease diagnosis and treatment with increased accuracy, speed, and individualization. Through the capability to process enormous amounts of medical data, healthcare professionals can make informed decisions, and patients enjoy better outcomes. AI is applied widely in all branches of medicine, including radiology, oncology, cardiology, neurology, and personalized medicine.

Figure 2: Overview of Key AI Technologies in Healthcare and their Application

3.2.1. AI in Medical Imaging and Radiology

Medical imaging is most likely to be the most significant area where AI has evolved significantly. AI-based image technology assists radiologists in identifying abnormalities more accurately and at a faster rate than human diagnostic mechanisms. Machine learning algorithms, and particularly deep learning-based convolutional neural networks, are capable of diagnosing tumors, fractures, infections, and other pathology from X-rays, MRIs, CT scans, and ultrasounds. For instance, algorithms based on computers that use AI have been developed to detect lung nodules on chest X-rays in early lung cancer detection. For another instance, AI-based mammography screening for the detection of breast cancer at an early stage with a high success rate of cure is possible (Pinto-Coelho, 2023).

3.2.2. Artificial Intelligence in Cancer Treatment and Oncology

Artificial intelligence has been highly beneficial in oncology since it helps in diagnosing cancer, planning its treatment, and designing drugs. Pathology slides are analyzed with the help of artificial intelligence software that can detect cancer cells better than any conventional method. Through these programs, pathologists are able to identify tumor characteristics, determine cancer aggression, and forecast its progression. Artificial intelligence makes possible the practice of precision oncology based on genetics and molecular analysis and the provision of personalized treatment options. AI-enabled platforms like IBM Watson for Oncology analyze huge amounts of scientific papers and data about cancer patients to offer personalized treatment suggestions (Dlamini *et al.*, 2022).

3.2.3. AI in Cardiology

Among the various diseases affecting people all around the globe, CVDs are considered major causes of fatalities and can be managed by using AI technology. Computer-assisted analysis of ECG assists in detecting problems in the heart rate of individuals, such as atrial fibrillation, before developing into major complications. It also enables the prediction of a heart attack in the wake of assessing the associated risks in light of cholesterol level, blood pressure, and behavior pattern. One more diagnostic approach for cardiology that has been revolutionized by AI algorithms is echocardiography (Sahay & Wadhwani, 2022). AI predictive models analyze patient information to give an estimate of the probability of heart disease, and preventive intervention and lifestyle modification are employed to reduce cardiovascular risk.

3.2.4. AI in Neurology and Brain Disorders

AI has revolutionized neurology immensely with improved diagnosis and treatment of brain diseases such as Alzheimer's disease, Parkinson's disease, epilepsy, and multiple sclerosis. MRI and PET scan interpretation by AI identifies warning signals of neurodegenerative diseases at an early stage, which can be prevented by early interventions that can stop the progression of the disease. In treating epilepsy, seizure prediction models incorporating AI analyze EEG information and identify patterns to anticipate and alert before a seizure (Awuah *et al.*, 2024). AI is also being used to develop brain-computer interfaces (BCIs) to enable paralysis or neurologic impairment to communicate. These interfaces translate brain signals into electronic commands and allow patients to use them to control devices with their minds.

3.2.5. AI in Personalized Medicine

Precision medicine, or personalized medicine, applies the genetic, environmental, and lifestyle features of individual patients to customize treatment. AI facilitates personalized medicine by searching through huge repositories of genomic data to identify disease-inducing genetic mutations and offer targeted treatment. AI predictive models of drug response inform the most effective treatment per patient, reduce side effects, and improve curative effects. Pharmacogenomics, the science of understanding drug responsiveness in terms of genes, has been greatly facilitated by AI (Taherdoost & Ghofrani, 2024). Artificial intelligence systems use machine learning to analyze genetic profiles to predict the likelihood of an individual patient metabolizing a given drug so that physicians can prescribe the type and quantity of drug most effectively. Thus, trial-and-error prescribing is prevented, and patients are safer.

3.2.6. AI in Surgery and Robotic Procedures

Surgical procedures with robotics and AI functions have been most successful in the upgrading of minimally invasive surgery through the use of precision, stability, and decision support in real time. Robot-assisted surgical systems, like the da Vinci Surgical System, take advantage of AI algorithms to enhance surgeons' skills for more accurate surgery and reduced recovery time. Artificial intelligence-powered robot platforms review surgical videos with real-time feedback, reducing the risk of error and enhancing patient outcomes (Iftikhar *et al.*, 2024). Preoperative planning is also performed with AI since surgical procedures are simulated virtually using patient-specific anatomical data. Surgeons then have the option to plan and optimize surgical technique prior to carrying out the procedure. Surgeons are also augmented by AI-powered AR technology that superimposes digital information onto the anatomy of the patient, enhancing visualization and guidance during complex surgery (Figure 3). From a HEOR perspective, these applications reduce diagnostic costs, improve cost-effectiveness, and support value-based healthcare decision-making.

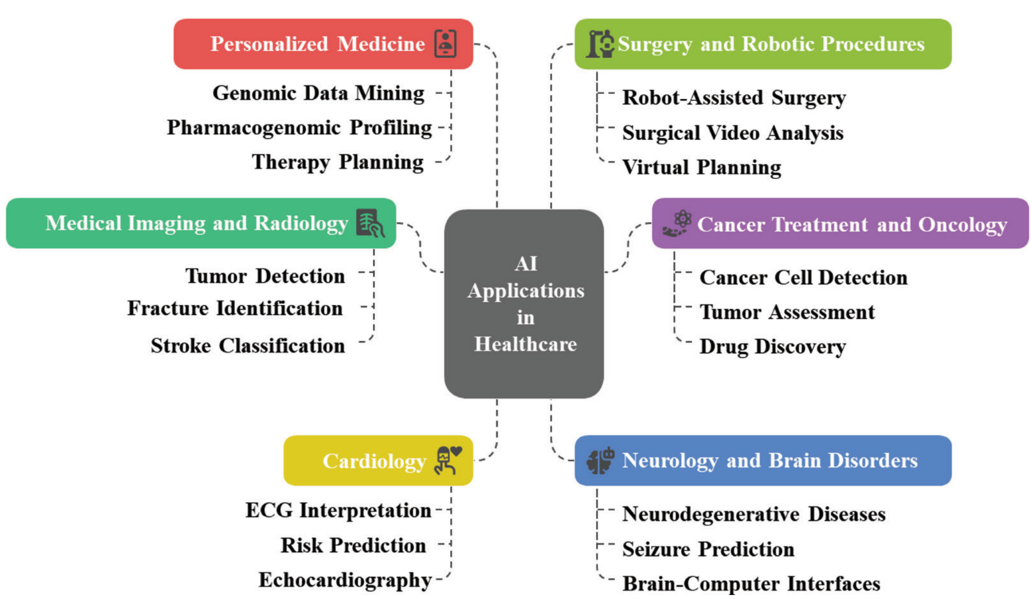

Figure 3: AI Applications in Healthcare

4. Economic Evaluations by AI in Healthcare

4.1. Overview of Economic Evaluations

The health economic assessment process requires the evaluation of the worth and expenses of healthcare initiatives, including AI-based technology. With the ongoing development of the healthcare sector through AI, it is essential to explore the economic aspects of such initiatives to ensure cost-effectiveness and efficiency (Al Meslamani, 2023). The economic appraisal is an objective approach to quantifying the cost and effects associated with implementing artificial intelligence strategies that will enable policymakers, health practitioners, and payers to make prudent decisions regarding the efficient use of their funds. The primary objective of conducting economic appraisal is to determine whether artificial intelligence techniques are relatively more cost-effective than conventional approaches. Artificial intelligence has the potential of reducing costs of providing healthcare services through the automation of bureaucratic procedures, improvement in diagnostic rates, decrease in medical errors, and early disease detection. However, the initial investment involved in implementing AI strategies, such as development and training, may be inevitable. There are different methodologies used in conducting economic analysis of AI in health (Voets *et al*., 2022). They include cost-effectiveness analysis (CEA), cost-utility analysis (CUA), cost-benefit analysis (CBA), and budget impact analysis (BIA). They all provide different types of information about the dollar and healthcare cost of the impact of the implementation of AI. Overall appraisal needs to include consideration of not just direct cost of healthcare, but indirect expense as well, along with indirect social effects such as heightened productivity and lowered burden to caregivers.

4.2. Cost-Effectiveness Analysis of AI Interventions

Cost-effectiveness analysis (CEA) is also one of the techniques of economic value estimation of AI-based healthcare intervention used most often. CEA is a calculation of cost and health outcome of AI technology compared to conventional medical intervention. Cost per unit of health gain, i.e., cost per diagnosis, cost per avoided hospitalization, or cost per life-year gained, is the primary measure of outcome when applying CEA. AI has been of undreamed benefit in augmenting the precision in diagnosis and early detection of disease, and this has resulted in unbelievable cost savings by way of complication and hospitalization avoidance (Khanna *et al*., 2022). For instance, artificial intelligence programs in radiology can correctly identify diseases such as lung cancer, stroke, and heart disease without the need for further tests or procedures. In doing so, AI will make it possible to enhance the utilization of healthcare resources by ensuring proper and timely interventions.

A classic example of reducing costs through AI includes diabetic retinopathy screening. This involves having medical experts examine retinal scans, a process which can be costly both in terms of time and resources. However, the use of AI for screening can scan many retinal images quickly without the need for experts and allow diabetic retinopathy to be detected early. Studies carried out economically show that the use of AI for screening reduces the costs involved (Hossain *et al*., 2024). Other places in which AI interventions have been found to be cost-effective include the prediction of hospital admissions and prevention thereof using artificial intelligence technology. AI algorithms analyze patients' data and determine the patients who are most at risk of being re-admitted to hospital. In this case, intervention measures such as personalized post-discharge care and tele-monitoring are put in place to prevent the unnecessary readmission of patients into hospitals, thereby cutting down on healthcare expenses and enhancing patient well-being. However, when assessing the cost-effectiveness of AI interventions, one must take into account the expected negative impacts associated with the use of AI (Shiwlani *et al*., 2024). Substantial investment must be made before implementing AI in order to construct proper infrastructure, ensure cybersecurity measures, and train employees. Furthermore, the benefits that come with the implementation of AI technology will not be realized until the future, meaning that economic considerations must be made regarding both initial costs and future benefits.

4.3. Methodological Approaches in Economic Evaluations

Economic analysis of AI-driven health interventions requires robust methodologies in order to identify proper and credible outcomes. Cost-effectiveness analysis (CEA), cost-utility analysis (CUA), cost-benefit analysis (CBA), and budget impact analysis (BIA) are the most common methodologies used. All these methodologies provide varied views regarding the economic cost of embracing AI in healthcare.

4.3.1. Cost-Utility Analysis (CUA)

Cost-utility analysis (CUA) is a form of CEA where quality-adjusted life years (QALYs) or disability-adjusted life years (DALYs) are employed as the measure of outcome. CUA is particularly appropriate in the evaluation of AI interventions with an effect on length and quality of life. CUA is most often applied by health policymakers to determine whether new AI technology is value for money. For example, artificial intelligence-based oncology decision support systems tailor cancer treatment by analyzing genetic information to predict responses of patients to various therapies (Scope *et al*., 2022). They enhance survival and minimize the adverse effects of useless treatments by making better treatment selection. CUA can ascertain whether the benefits in patient quality of life and survival are justified by the expense of implementing AI-based precision medicine.

4.3.2. Cost-Benefit Analysis (CBA)

Cost-benefit analysis (CBA) expresses both the benefits and the costs in terms of monetary amounts, enabling a direct comparison between AI interventions and conventional healthcare strategies. CBA is appropriate when there is thought of using AI technologies with economic gains as well as direct healthcare cost savings, such as improved workforce productivity or less caregiver burden. For example, AI mental health chatbots offer low-cost and convenient psychological therapy for depression and anxiety patients (Neogi *et al*., 2024). By reducing the need for face-to-face interactions, such AI technologies reduce healthcare costs while allowing people to stay engaged in their business and personal life. A CBA can ascertain whether economic benefits from enhanced mental health outcomes outweigh AI chatbot installation costs.

4.3.3. Budget Impact Analysis (BIA)

Budget impact analysis (BIA) evaluates the cost implications of implementing AI technologies in a given healthcare system or payer setting. In contrast to CEA and CUA, which are long-term in their outlook on cost-effectiveness, BIA is short-term in its outlook on affordability in AI interventions. This is especially relevant to healthcare insurers and governments in making decisions on whether or not to reimburse (Smith & Levy, 2024). For example, administrative automation using AI, such as robotic process automation (RPA) for insurance claims handling, reduces administrative costs and accelerates payment approvals. A BIA will help determine whether the cost savings accruing from automation enabled by AI are worth the upfront investment required to implement these technologies.

Few challenges have been generated, taking into account the growing use of AI in healthcare. Some of them include the lack of a standard method to quantify the cost-effectiveness of AI. AI technologies are developing so quickly that it is difficult to create long-term evidence of their economic effects. AI models also need to be updated and calibrated on a regular basis, which can introduce variability into cost-effectiveness estimates (Qin *et al*., 2024). AI implementation and the protection of data and privacy come next. For AI application in healthcare systems, massive amounts of data are used, hence raising issues regarding patient confidentiality and regulatory compliance. The importance of proper governance of data during economic analyses cannot be understated to try and earn regulatory approval and preserve public trust. As time passes and technology advances, the economic analyses of AI must take into account the social repercussions of such technologies. Automation through AI can help ease administrative processes and even lead to better clinical outcomes, but it may also endanger certain jobs within the healthcare sector. Here, regulators must weigh out both economic and job considerations before undertaking the implementation of AI (Figure 4) (Esmaeilzadeh, 2024).

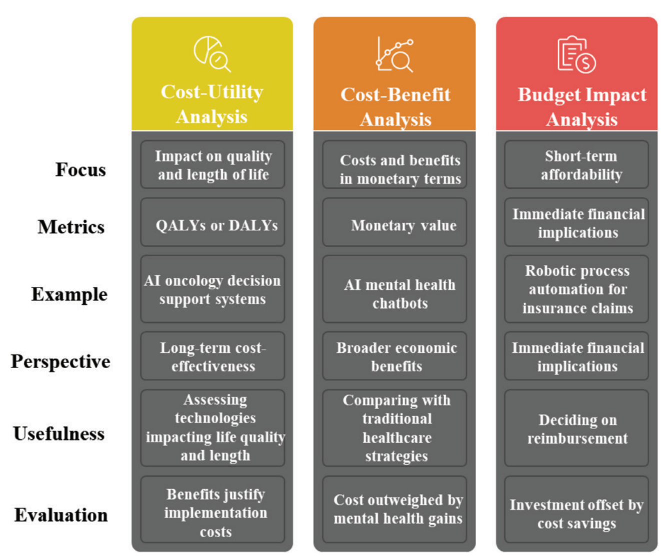

Figure 4: Methodological Approaches in AI Healthcare

5. Artificial Intelligence in Health Economics and Outcomes Research

Healthcare economics and outcomes research (HEOR) have seen great changes in terms of the pace of innovation brought about by artificial intelligence (AI). The application of machine learning, predictive analytics, and natural language processing through AI is changing the way health institutions view patient outcomes as well as the quality of life in healthcare delivery. In this paper, AI will be evaluated for its influence on patient care improvement, quality-of-life measurements, and practical examples of its application in healthcare.

5.1. Improvement in Patient Outcomes

The application of artificial intelligence in medical diagnosis and treatment has been revolutionary in improving patient results, thanks to its ability to predict the onset of disease, personalize therapy for each person, and maximize chronic disease management. AI models that have been trained on extensive amounts of data can recognize patterns to diagnose illnesses that are complicated to detect and treat, such as cancer, diabetes, and heart disease. For instance, AI imaging technology can now be more effective than radiologists in spotting irregularities in medical images to prevent erroneous diagnoses and allow quick action to boost patients' chances of surviving. Additionally, AI predictive analytics is revolutionizing how healthcare practitioners anticipate and manage illnesses (Ren *et al*., 2022).

One such example is the diagnosis of sepsis using AI. This condition is often not diagnosed unless it gets severe to a certain extent. Using AI, it is possible to diagnose probable factors behind sepsis, and therefore doctors will be able to prevent its onset before it becomes critical. The truth has been proven by facts that such predictive methods result in decreased deaths within hospitals because the interventions become timely and accurate. Another field in which there has been an advancement in the field of health through the use of AI is AI robot-assisted surgeries (Iftikhar *et al*., 2024). For example, the Da Vinci robotic surgical system is extensively used in minimally invasive surgery procedures, offering more accuracy and effectiveness compared to conventional surgeries.

AI technology is equally transforming drug administration and adherence. Patients are enabled to take drugs on time and accurately through mobile applications and artificial intelligence-based bots by receiving alerts regarding the timing of drug use, observing potential drug side effects, and recommending appropriate dosages. AI-based apps analyze medical records and clinical texts to identify trends associated with medication adherence or adverse effects of the drugs to help physicians administer the medications appropriately. One-on-one attention has proven effective in managing long-term illnesses such as diabetes and hypertension, where drug adherence must be ensured (Ogbuagu *et al*., 2023).

5.2. Quality of Life Assessments

AI technology has also helped in enhancing and assessing the quality of life of patients using new techniques. Conventional assessment of quality of life was through patient-reported outcomes, PROMs, which were beneficial, yet rarely used to obtain real-time and objective information. With AI-powered wearable devices, the process has been enhanced to provide continuous and objective measurements on health factors like heart rate, activity levels, sleep quality, and even blood glucose level. Such devices help in assessing the general well-being of patients and how well they are able to function every day (Kelly *et al*., 2025).

The use of AI for sentiment analysis is increasingly becoming one of the key factors behind patient experience and psychological well-being. With the use of sentiment analysis on social media platforms, patient forums, and electronic medical records, AI can identify the existence of emotional states and mental issues that would otherwise remain undetected without the presence of AI in the medical setting. Indeed, machine learning models have been applied in processing patient interactions and detecting depression and anxiety indicators.

Furthermore, AI enhances quality-of-life index development by integrating information from multiple sources, including physiological markers, patient self-report, and health outcomes. Such discoveries allow clinicians to develop more efficacious and individualized treatment regimens that address not only patients' physical well-being but also their emotional and social status (Jannani *et al*., 2024). For instance, digital health assistants based on artificial intelligence provide cognitive behavioral therapy (CBT) techniques to patients with mental illnesses or stress so that they can improve their quality of life without necessarily needing continuous face-to-face sessions with a therapist (Figure 5).

5.3. Case Studies Demonstrating AI's Impact

5.3.1. AI for Diabetic Retinopathy Screening

One of those uses of AI is in the preclinical diagnosis of diabetic retinopathy (DR), which is one of the main causes of diabetic patients losing their sight. In all underserved groups, ophthalmologists are not common, resulting in delays in diagnosis and treatment. Artificial intelligence-powered image analysis software, including Google's DeepMind and

IDx-DR, have already been used to scan retinal images for signs of diabetic retinopathy as well as trained professionals. From a HEOR perspective, AI-based diabetic retinopathy screening has demonstrated substantially lower cost per case detected compared to traditional ophthalmologist-led programs, with direct implications for reimbursement policy and coverage decisions in resource-limited settings (Grzybowski *et al*., 2023).

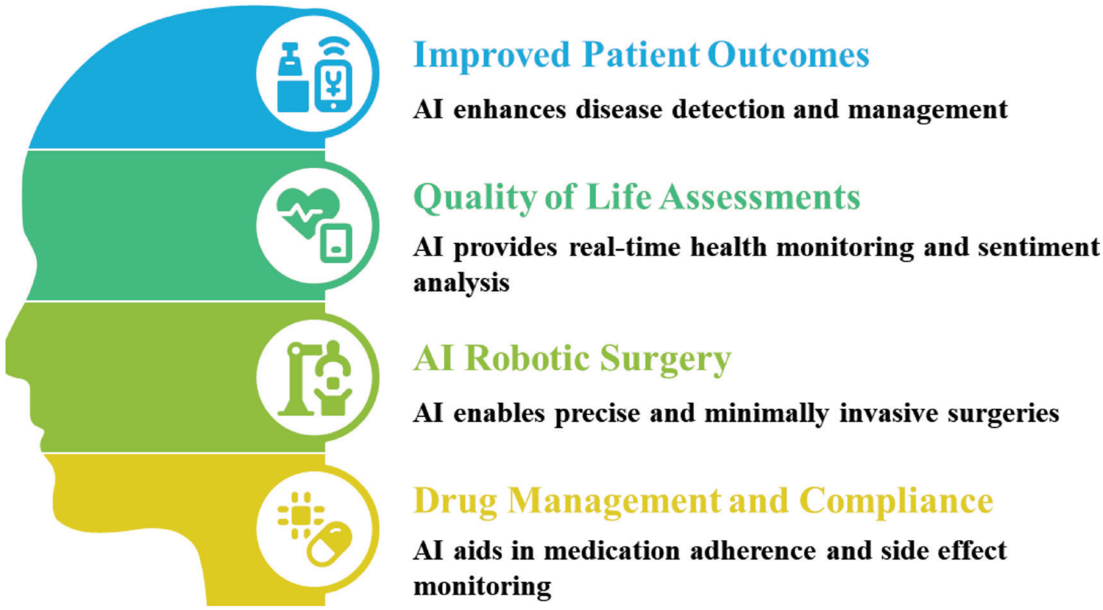

Figure 5: Impact of AIs on Healthcare

5.3.2. AI in Oncology and Precision Medicine

Artificial Intelligence is also quite advanced when it comes to the treatment and diagnosis of cancer using Genomic Medicine. AI technologies such as IBM Watson for Oncology scour through all available medical journals and even clinical studies to come up with tailored treatment plans for patients diagnosed with cancer. With the help of Artificial Intelligence and the identification of certain genetic mutations, doctors are able to come up with a personalized plan of action for their patients. These precision oncology applications carry significant HEOR implications: by reducing ineffective treatments and associated toxicity management costs, AI-guided therapy selection can improve the cost-utility ratio and support value-based reimbursement frameworks for oncology drugs (Khan *et al*., 2024).

5.3.3. AI in Stopping the Opioid Crisis

AI technology has shown its impact in another highly important field, namely, putting an end to the opioid epidemic. Predictive algorithms based on AI have started being used for identifying high-risk individuals prone to developing an addiction to opioids based on their previous health records, drug prescription records, and socio-economic profile. Identifying such individuals makes it possible for block-chain physicians to treat pain using alternate means (Johnson *et al*., 2023). Moreover, artificial intelligence-powered chatbots such as Woebot and Replica deliver constant psychological support and advice to individuals battling substance abuse disorders, reducing their chances of relapsing and improving their well-being.

5.3.4. AI in Hospital Operations and Healthcare Resource Allocation

Moreover, artificial intelligence is helping to increase the efficiency of hospitals and improve their efficacy. Hospitals use predictive tools of scheduling in order to forecast patient flow data, thus allocating resources appropriately and minimizing waiting time. Machine learning techniques are applied for the analysis of historical data on patient flow in order to allocate beds, staff schedules, and operating rooms effectively (Shamsi, 2024). The implementation of AI-based management operations within hospitals has been associated with better satisfaction scores among patients, reduced cases of hospital-acquired infections, and enhanced healthcare effectiveness.

Even though there are many advantages of using AI in medicine, there are certain ethical and practical considerations when using AI in health economics and outcomes research. One such challenge is data protection, as AI systems depend heavily on patient data for making decisions. HIPAA and GDPR laws must be adhered to without violating patients' privacy. Another concern is the creation of biased AI models, which will lead to bias in outputs, creating disparities in the field of health. This is why efforts are being made to ensure that the AI model learns from different populations and diseases (Nazer *et al*., 2023).

6. Challenges and Limitations of AI in HEOR

Artificial Intelligence (AI) has played an instrumental role in HEOR, enhancing patient care, improving operations, and decision-making. Yet, while the enormous potential that AI holds in transforming the landscape is undeniable, there are equally many obstacles and limitations that stand in the way of successfully adopting AI technology in healthcare. Among the most significant are data security and privacy problems, algorithmic biases and their consequences, and difficulties with introducing AI into today's healthcare settings. Identifying and addressing these limitations is crucial for delivering ethical and equitable outcomes from AI.

6.1. Data Security and Privacy Concerns

Another important issue regarding the use of AI in health economics and outcomes research is that of privacy and confidentiality. There are several types of data used by AI algorithms, such as EHRs, genomics, imaging, and physiologic data collected through wearable technology (Gabriel, 2023). While the information provides AI with the ability to produce relevant and useful data, several problems associated with privacy, consent, and misuse arise.

Among the foremost issues are data leaks and security breaches. Hospitals would serve as a prime target for such cyber-attacks due to the sensitive nature of patients' data. In the absence of adequate protection measures, any AI system may be hacked through such vulnerabilities, resulting in the theft of data, identity fraud, and even medical record manipulation. In 2020, over 29 million patient healthcare records were exposed (Herzog *et al*., 2024). The second problem regarding the protection of patient confidentiality when it comes to the patient group is that of sharing patient information without consent. Since AI systems require open access to a vast amount of data to improve the accuracy of predictions and functioning, patients remain uninformed about the sharing and use of patient information by a third party, which is also unethical from an ethical point of view, considering the issues of informed consent.

Moreover, AI models should be based on de-identified or anonymous data in order to reduce the possibility of violating patient confidentiality; however, according to various studies, it is possible to re-identify anonymous data sets by using two or more data sets. It is an unnecessary risk which might lead to the revelation of health information (Kathuria *et al*., 2024).

Also, compliance with laws on data protection such as GDPR in the European Union and HIPAA in the USA is a major threat to AI in HEOR (Tschider *et al*., 2024). These are highly stringent standards toward the collection, storage, and dissemination of information, an uphill battle for AI developers and healthcare systems to utilize patient data to its maximum without crossing legal boundaries. Balancing access to data for AI-powered information and rigid adherence to privacy legislation is a multi-sigma problem that healthcare actors need to overcome (Selvakumar *et al*., 2025).

6.2. Algorithmic Bias and Its Implications

Algorithmic bias is another critical AI limitation in HEOR since it can lead to imbalances in health outcomes. AI bias is created where training data used to create machine learning algorithms are non-representative of wide populations, leading to unbalanced or biased predictions that are injurious to specific demographic groups disproportionately (Siddique *et al*., 2023).

Undercounting minority and marginalized populations in medical information is probably one of the strongest root sources of bias. Clinically, clinical research and clinical trials up to now have been done in European populations, making AI models that are less accurate for patients of other racial, ethnic, or socioeconomic categories. For instance, the diagnostic tool used by AI trained to learn from data sets that have predominantly Caucasian patients can miss diagnosing some diseases in African American, Hispanic, or Asian patients, resulting in misdiagnosis or delayed diagnosis (Seyyed-Kalantari *et al*., 2021).

The second category of bias lies in the way healthcare systems have usually distributed resources. Healthcare models learned from historical healthcare choices will likely carry forward prior inequities unintentionally (Albahri *et al*., 2023). A forecasting AI model that forecasts outcomes for patients, for example, can devote fewer resources to poor patients if historical data indicate that they have worse outcomes due to systemic deficits as opposed to medical need (Gala *et al*., 2024).

Other issues with AI in healthcare include gender bias. Studies have demonstrated that AI algorithms for the detection of certain diseases like heart attack are not very accurate in diagnosing women because past data on which the AI algorithm was trained consisted mostly of men (Buslón *et al*., 2023). This would mean that patients who suffer from heart disease with uncommon symptoms have a higher likelihood of developing problems in diagnosis, which translates to poorer healthcare. The solution to mitigate such AI bias would entail a combination approach in the form of diversification of training sets and rigorous testing of AI algorithms for various populations (Krause, 2024). The collaboration between scientists and healthcare providers needs to be tight in order to train these artificial intelligence systems using diverse data sets and audit them for fairness before deploying them. Regulatory bodies, on the other hand, would have to set standards on how transparency can be included in these AI decisions and direct the model builders to explain how they developed and tested these systems (Ferrara, 2023).

6.3. Integration Challenges with Existing Systems

AI can play a transformative role in HEOR; however, the incorporation of AI solutions into existing healthcare delivery frameworks presents its own difficulties. Every single health system in the world has been constructed based on legacy systems, intricate processes, and disparate data sources. Interoperability, or the ability of various healthcare delivery systems to exchange information, is just one of many obstacles (Kusumawati, 2025). It is usual for most healthcare institutions to have customized EHR systems with patients' data presented in different ways, making it difficult for AI to access and process data easily. Absence of standardized methods of data entry, incomplete data, and multiple coding systems make it hard to integrate AI into the process (Akhtar, 2024).

The first challenge facing the use of AI models is the requirement for standardized and unified databases to ensure proper functionality. However, this poses an enormous task for healthcare organizations. The other challenge is the reluctance on the part of medical practitioners to adopt AI models. Most medical practitioners and doctors tend to be reluctant about adopting AI-driven models because they think (Yousif *et al.*, 2024). The third issue is the explainability of AI, as a result of which most machine learning algorithms become "black boxes," which produce results without explaining how they are arrived at. Thus, this difficulty in understanding makes it difficult for healthcare workers to trust the conclusions drawn by AI (De Panfilis *et al.*, 2023).

Moreover, AI adoption requires significant expenditure and technical expertise beforehand. The design and implementation of AI-driven solutions involve spending aspects regarding data infrastructure, data scientists to train AI algorithms, data scientist recruitment, and the re-engineering of the current system to incorporate AI-driven functionality. Most healthcare facilities do not have the financial and technical capacity to implement AI-powered solutions on a wide scale, particularly when operating under difficult resource constraints (Jaber, 2023). If there is no huge investment in artificial intelligence infrastructure, most organizations will fail to tap into the full potential of artificial intelligence.

Moreover, ethics and regulations complicate matters when integrating artificial intelligence. There must be rigorous testing of any artificial intelligence system to confirm that it is safe, accurate, and regulatory compliant (Aderibigbe *et al.*, 2023). However, it is worth noting that gaining approval for artificial intelligence-powered devices and decision-making systems is quite time-consuming and acts as a disincentive when it comes to implementation on a wide scale. Additionally, in other cases, differences in regulatory structures in various countries lead to an additional barrier in the application of AI technology, necessitating modifications in line with regional regulations.

For such integration challenges to be overcome, healthcare facilities must prioritize interoperability, ensuring data standardization while fostering cooperation between healthcare practitioners and artificial intelligence developers. By training healthcare professionals in artificial intelligence literacy and involving them in the development process, confidence in adopting AI technologies will increase. Governments and healthcare organizations are also forced to invest in the digital infrastructure necessary for AI implementation and offer financing options to pursue R&D on AI (Figure 6) (Esmaeilzadeh, 2024).

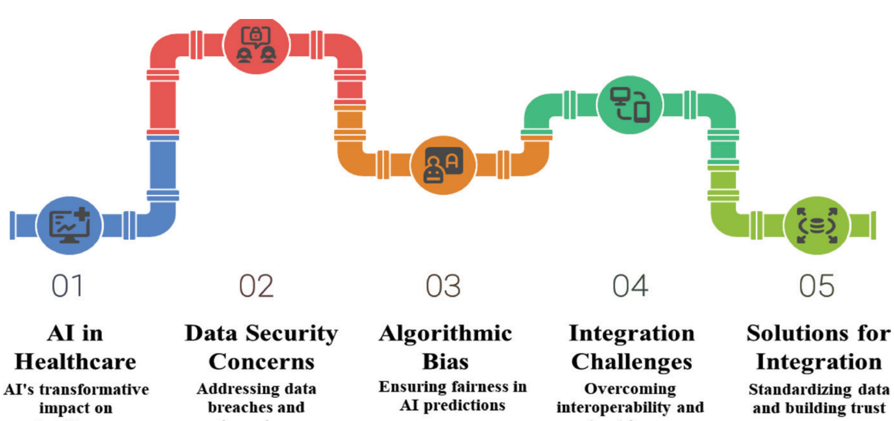

Figure 6: Challenges and Limitations of AI in HEOR

7. Future Directions for AI in Health Economics and Outcomes Research (HEOR)

Artificial intelligence (AI) has had tremendous success till now in health economics and outcomes research (HEOR), specifically in improving the results obtained by patients, maximizing healthcare resources, and helping with decision-making processes. However, there is still a long way to go for AI, since further developments will make it even better. Through the development of new AI technology, AI has the potential to transform the field of HEOR through improved AI methodologies, increased automation of economic modeling, and advanced research methodology (Boni *et al*., 2024).

7.1. Innovations in AI Technologies

The development of artificial intelligence technologies is progressing at an extremely rapid pace, and the application of these technologies to the field of HEOR will increase significantly in the future as machine learning, deep learning, NLP, and reinforcement learning become more sophisticated. These technologies will further develop HEOR methodologies and techniques and help make more accurate decisions based on data analysis.

The most critical breakthrough of AI that will revolutionize HEOR is XAI technology. The majority of current AI models, especially deep learning models, can be regarded as "black box" technology because they provide prediction results but do not explain how these predictions were made (Hassija *et al*., 2024). It is extremely important for transparency in HEOR to instill a sense of trust amongst the key stakeholders. With explainable AI, scientists can understand how an artificial intelligence model makes its decisions and how it processes the available data, increasing the credibility and accountability of AI-driven economic forecasting and predictions (Faheem *et al*., 2024).

A recent innovative advancement is the application of federated learning in HEOR studies. AI models require a lot of data gathered at one point in order to be trained, and that makes it hard for the data on a privacy and security front. Federated learning ensures that machine learning models can be trained through diverse distributed systems without having to move any data away from its source. Patient data privacy is protected while still enabling machine learning models to leverage a huge amount of medical data (Whang *et al*., 2023). Federated learning is set to enhance the generalizability of AI-generated evidence, allowing for evidence-based policy-making in healthcare.

Besides, AI will feature more prominently in RWE, which is an evolving sub-discipline within HEOR. AI technologies will have the capacity to analyze vast amounts of unstructured data generated by EHRs, social media platforms, wearable devices, and PROs to generate meaningful insights about the effectiveness of medical interventions in real-world scenarios (Delaroziere *et al*., 2024). Such RWE analysis will play a role in shaping healthcare policies, medication pricing policies, and reimbursements through increasingly patient-centered, all-encompassing evaluations of outcomes of treatment.

In addition, the use of multimodal convergence in AI will improve HEOR studies, as such technology will allow for an analysis of different kinds of data at once. That is, AI will facilitate the simultaneous analysis of documentation, imaging data (such as MRIs and CT scans), genomic data, and patient monitoring data (Mese *et al*., 2023).

7.2. Potential for Automation in Economic Modeling

Another pillar of HEOR is economic modeling, which provides analyses such as cost-effectiveness studies, budget impact, and health policies. With AI, it is possible that economic modeling will be automated in almost all aspects. The result would be faster, more accurate, and adaptive analysis relative to changing circumstances.

The most promising application of AI to economic modeling is automating cost-effectiveness analysis (CEA). Classic CEAs require time-consuming manual collection of data, assumptions, and sensitivity analysis to compare the cost and value of alternative treatments (Challoumis, 2024). AI systems can quickly analyze massive sets of data, identify relevant variables, and conduct live simulations to forecast the long-term cost-effectiveness of medical treatments. Machine learning algorithms can further advance cost-effectiveness models by uncovering concealed patterns between treatment variables and economic outcomes, making them more accurate and data-based for decision-making.

Artificial intelligence-driven predictive analytics will keep enhancing economic modeling to the point of making more accurate estimates of the cost of healthcare. Through the analysis of patient history and health expenditure patterns, AI will calculate future healthcare expenditure in various situations so that policymakers can better allocate resources. The models will also assist drug companies and insurers in offering reasonable pricing methods for new drugs and treatments by taking various real-world variables impacting treatment prices into consideration (Valle-Cruz *et al*., 2022).

Furthermore, NLP algorithms driven by AI will transform the way economists are able to pull economic data from scientific journals, regulatory filings, and clinical trial publications. Economic modelers have traditionally had to search through thousands of papers to find relevant cost and outcome data. NLP-based AI systems are capable of carrying out this activity automatically by reading large amounts of text, extracting relevant economic data points, and synthesizing the data into structured datasets for economic modeling (Abir *et al*., 2024). Automation will also save literature reviews and meta-analyses considerable time and effort, enabling HEOR professionals to build insights more rapidly and effectively.

Healthcare decision modeling is another space where AI will automate. Decision trees, Markov models, and AI-based agent-based simulations will assist researchers in creating more dynamic and flexible economic models. These AI models would continually upgrade themselves based on any new data coming from the real world, and healthcare policymakers would always be using the latest information available to them when making decisions about policy changes or reimbursement changes (Abir *et al*., 2024).

AI-driven automated scenario testing will also enable researchers to simulate various policy and economic scenarios more accurately. AI can create and simulate several thousand types of healthcare policy interventions and economic approaches in minutes compared to using conventional modeling methods (Ramezani *et al*., 2023).

8. Conclusion

The introduction of Artificial Intelligence (AI) in Health Economics and Outcomes Research (HEOR) is now considered to be a game-changer that can help make healthcare-related decisions, healthcare resource allocation, and healthcare outcomes more efficient. As per this discussion, AI-based tools such as machine learning, deep learning, and natural language processing (NLP) have become even more essential to support HEOR research through greater efficiency and accuracy. With the analysis of huge volumes of data available from the real world of healthcare, AI is helping in making healthcare systems data-driven.

For all these benefits, however, AI use in HEOR has not been without difficulties, from data privacy concerns to algorithmic bias concerns, integration issues, and ethics. Though the future of artificial intelligence is promising, challenges must be overcome in order to reap the most benefits and have fair and open healthcare decision-making.

Application of AI in HEOR is transforming healthcare interventions' evaluation and analysis for economic value and patient outcomes. Maybe the biggest strength of AI is its capability to perform sophisticated economic analysis with less time and effort expended through traditional cost-effectiveness analysis. AI-based predictive models have the potential to forecast healthcare expenditure, support treatment patterns, and guide policymaking on healthcare policy through examination of actual-world evidence (RWE) at hitherto unimaginable levels of detail. Through examining immense amounts of data in EHRs, clinical trials, and patient feedback, AI is helping improve the accuracy of health economic models and bringing more light to the effectiveness of treatment and long-term health outcomes.

Furthermore, AI is making an indispensable input to healthcare outcomes research through demonstrating patterns and correlations hard to unveil using traditional analyzing tools. Diagnostics powered by AI, as well as patient-focused medicine paradigms, are empowering faster diagnosis of diseases, enhanced medication adherence, and targeted treatments that ultimately improve patient results at reduced healthcare expenses. Monitoring quality of life has also become advanced, with AI-driven solutions monitoring patients in real time and allowing intervention at the appropriate time, as well as care of chronic illnesses to a much greater extent. It has been evident through case studies how AI can make a difference to patient care, particularly in oncology, cardiology, and psychiatric care, where early detection and tailored regimen treatment can be life or death.

While such advantages can be found, applications of AI in HEOR are plagued by several issues. Data security and patient privacy are a strong impediment because infrastructure for AI would require access to large volumes of sensitive patient data. Remaining consistent with acts such as HIPAA and GDPR without compromising the integrity of the data and patient confidentiality continues to be challenging. Algorithmic bias is also a problem since AI models based on unrepresentative datasets may reinforce healthcare biases and lead to uneven recommendations. Moreover, the application of AI to healthcare systems is fraught with problems owing to the patchy character of the health data infrastructure, as well as reluctance among some healthcare professionals to bank on AI-supported decision support systems. These issues will have to be met by concerted efforts of regulatory agencies, AI developers, policymakers, and healthcare professionals to establish ethical norms and increase trust and transparency in AI-driven healthcare products.

Abbreviations

AI: Artificial Intelligence; **BCI:** Brain–Computer Interface; **BIA:** Budget Impact Analysis; **CBA:** Cost–Benefit Analysis; **CBT:** Cognitive Behavioral Therapy; **CEA:** Cost-Effectiveness Analysis; **CNN:** Convolutional Neural Network; **CT:** Computed Tomography; **CUA:** Cost-Utility Analysis; **CVD:** Cardiovascular Disease; **DALY:** Disability-Adjusted Life Year; **DL:** Deep Learning; **DR:** Diabetic

Retinopathy; **ECG:** Electrocardiogram; **EHR:** Electronic Health Record; **EMR:** Electronic Medical Record; **EEG:** Electroencephalogram; **EQ-5D:** EuroQol Five-Dimension Questionnaire; **GDPR:** General Data Protection Regulation; **HEOR:** Health Economics and Outcomes Research; **HIPAA:** Health Insurance Portability and Accountability Act; **HRQoL:** Health-Related Quality of Life; **HTA:** Health Technology Assessment; **ICER:** Institute for Clinical and Economic Review; **ML:** Machine Learning; **MRI:** Magnetic Resonance Imaging; **NICE:** National Institute for Health and Care Excellence; **NLP:** Natural Language Processing; **PET:** Positron Emission Tomography; **PRO**: Patient-Reported Outcome; **PROM:** Patient-Reported Outcome Measure; **QALY:** Quality-Adjusted Life Year; **RCT:** Randomized Controlled Trial; **RNN:** Recurrent Neural Network; **RPA:** Robotic Process Automation; **RWD:** Real-World Data; **RWE:** Real-World Evidence; **SF-36:** Short Form-36 Health Survey

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Authorship Contribution

Saksham Sharma contributed to conceptualization, literature review, and manuscript drafting; Shushank Mahajan contributed to study design, supervision, manuscript review, and editing; Sanjana Mehta contributed to literature search, data curation, and manuscript writing; Shrey Partap Singh contributed to data collection, literature review, and manuscript drafting; Sakshi Sharma contributed to reference management, data organization, and manuscript editing; Samrat Chauhan contributed to critical review, data validation, and manuscript revision; Sanchit Dhankhar contributed to literature search, manuscript formatting, and proofreading. All authors contributed to the revision of the manuscript, approved the final version, and agreed to be accountable for all aspects of the work.

Ethical Approval

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Declarations

The authors confirm that this manuscript is original, has not been published previously, and is not under consideration for publication elsewhere. The final version of the manuscript has been approved by all authors.

Conflict of Interest

The authors declare that there is no conflict of interest regarding this manuscript.

Data Availability Statement

Data sharing is not applicable to this article, as no new data was generated or analyzed.

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AI Disclosure Statement

The authors declare that artificial intelligence (AI)-assisted tools were used solely for language enhancement, grammar checking, and improving the readability of the manuscript.

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