



Evaluating the Impact of Artificial Intelligence on Medical Physics: A Review

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Abstract

Artificial Intelligence (AI) has proven to be a source of innovation in all aspects of technological, scientific, and medical advancement, Medical Physics is not excluded, driving advancements in medical imaging, treatment planning, diagnostics, and patient outcomes. . This study reviews the impact of AI on medical physics, with an analysis of recent developments and their clinical implications. A thorough search was conducted across multiple databases, including Google Scholar, PubMed, ResearchGate, and IEEE Xplore. The search was conducted using keywords related to AI and medical physics, including "artificial intelligence," "machine learning," "deep learning," "medical imaging," "treatment planning," "diagnostics," and "patient outcomes". The search focused on studies published from 2016 to 2024 that examine the implementation and effectiveness of AI technologies. This review highlights AI's ability to transform medical physics, especially in the aspects of medical imaging, diagnosis, treatment planning, and patient outcomes, emphasizing the need for continued research and integration of AI technologies in clinical practice. The study suggests future research in the area of data privacy concerns and standardized protocols, to fully harness AI's benefits in medical physics.

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1.0 Introduction

Artificial Intelligence (AI) is at the forefront of technological advancements across numerous fields, with healthcare being one of the most significantly impacted areas (Xing *et al.*, 2021). AI can be described as the development and utilization of programs, algorithms, and systems that can carry out tasks that require human reasoning, intelligence, and problem-solving skills. Within healthcare, AI technologies are bringing about innovations that enhance the quality of diagnosis, treatment planning, patient care, and operational efficiency. According to Liu *et al.* (2023), the impact of AI in medical physics is enormous and capable of transforming the ways tasks are done in clinics.

Medical physics involves the practical application of physics principles and concepts in medicine, especially in the aspects of medical imaging, radiation therapy, and nuclear medicine. The integration of AI into these domains has opened new avenues for enhancing the precision, speed, and effectiveness of medical interventions. Zanca *et al.* (2021) highlighted the establishment of a working group by the 'European Federation of Organization for Medical Physics (EFOMP)' to integrate AI into the medical physicist curriculum. This initiative shows the growing importance of AI in the professional development of medical physicists, aiming to enhance their skills and knowledge in applying AI technologies effectively in clinical settings. Dong & Xing, (2020) and Fan, *et al.* (2020) showed that 'AI streamlines the workflow of radiation therapy planning, and automates dose calculations, considerably reducing the time needed to generate treatment plans'. Figure 1 illustrates the hierarchical relationship between AI, Machine Learning (ML), Deep Learning (DL), and neural networks as a key component of DL. This

framework demonstrates how AI-driven ML algorithms and DL techniques can be employed to enhance diagnostic imaging and optimize treatment planning, by leveraging advanced data analysis and pattern recognition capabilities.

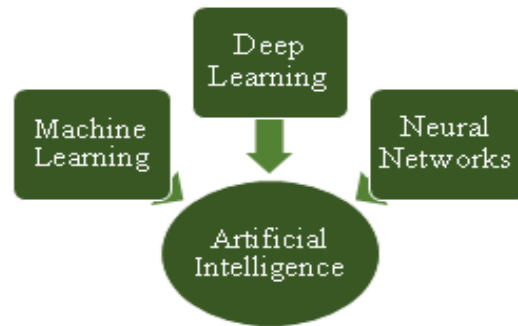


Figure 1: Components of Artificial Intelligence

This systematic review aims to synthesize current knowledge and provide insights into the future trajectory of AI in medical physics. The findings will inform practitioners, researchers, and policymakers about the advancements and potential areas for further exploration. By understanding the impact of AI on medical physics, stakeholders can better harness its capabilities to improve healthcare outcomes and enhance the quality of patient care. The review evaluates the impact of AI on medical physics, focusing on four key areas: medical imaging, treatment planning, diagnostics, and patient outcomes.

2.0 AI in Medical Physics

2.1 Medical Imaging

AI algorithms have rapidly changed and improved medical imaging by improving the quality and accuracy of image interpretation, diagnostic accuracy, efficiency, and patient care. The advent of AI through the development of deep learning algorithms has opened new avenues for improving accuracy, efficiency, and accessibility. Esteva *et al.* (2017) in their work

showed that when compared to the ability of experienced dermatologists to classify skin cancer, AI performed better with more accuracy and precision. This early and accurate detection drastically improves patient outcomes by enabling timely treatment. Similarly, Litjens *et al.* (2017) emphasized advancements in segmentation, detection, and classification tasks through deep learning, enhancing the precision and efficiency of image analysis, which is a crucial step in a medical procedure. McKinney *et al.* (2020) showcased AI's potential in breast cancer screening, where AI systems outperformed radiologists in identifying cancer in mammograms, thus improving early detection rates. Montero *et al.* (2021) and Diaz *et al.* (2021) further reviewed AI in medical imaging, with a focus on machine learning applications and the importance of image preparation, data curation, and annotation. These studies further

show the potential ability of AI to streamline workflows, reducing the time needed for image analysis and enabling faster diagnosis and treatment planning. Funama *et al.* (2021) demonstrated that conditional generative adversarial networks (cGANs) could generate high-quality computer tomography (CT) images, improving diagnostic accuracy and reducing radiation doses. According to Zhou *et al.* (2022), advancements in AI-driven radiotherapy planning, especially in integrating imaging data and optimizing radiation doses, have enhanced the precision of tumor targeting and treatment. Montalt-Tordera *et al.* (2021) and Zegers *et al.* (2021) also highlighted the benefits of machine learning in magnetic resonance imaging (MRI), improving image quality, reducing scan times, and enabling precise segmentation and classification.

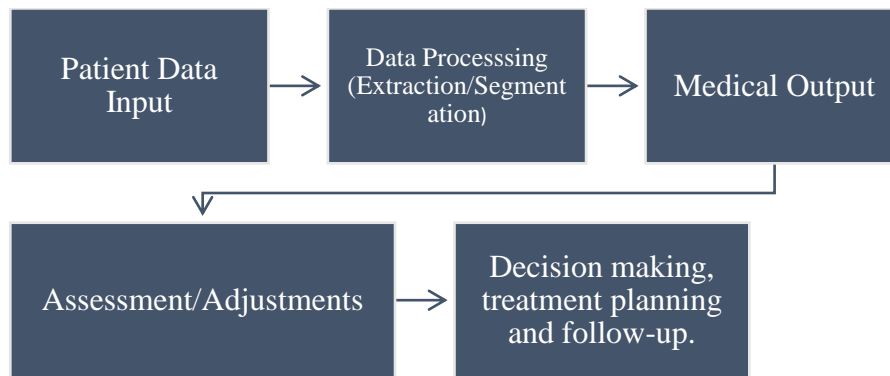


Figure 2: AI methodology in diagnostic and treatment process

2.2 Treatment Planning

AI has revolutionized treatment planning in radiotherapy by enhancing precision and personalization in patient care. Traditionally, treatment planning involves complex calculations to determine the optimal dose distribution that targets tumors while minimizing exposure to healthy tissues. However, these methods often rely on manual inputs and standard protocols that

may not fully account for individual patient variability. Figure 2 outlines how AI processes medical outputs to develop personalized treatment plans. This involves continuous assessments, evaluation, and adjustments to ensure effective treatment strategies follow-up. Nguyen *et al.* (2019) highlighted how AI-driven systems can improve dosimetry by analyzing patient data, including anatomical, physiological, and treatment history, to create more accurate

treatment plans. This improves radiation delivery accuracy, enhances treatment efficacy, and reduces side effects. Similarly, Boldrini *et al.* (2020) reviewed the application of AI in proton therapy, demonstrating improvements in dose distribution and treatment time. In their review, Boldrini *et al.* (2020) demonstrated how AI could enhance the precision of proton therapy by optimizing treatment parameters such as beam angles, energy levels, and dose constraints. Additionally, AI's ability to process data rapidly allows for real-time adjustments to treatment plans, maintaining effectiveness despite changes in tumor size or patient anatomy. This capability is crucial in adaptive radiotherapy, where plans are continuously updated. Moreover, AI streamlines the planning process by automating tasks like organ contouring and dose calculations, significantly reducing planning time and allowing clinicians to focus on complex decision-making aspects of treatment.

2.3 Diagnosis

Diagnosis is a critical component of healthcare, serving as the foundation for treatment decisions and patient management. AI is rapidly becoming a critical tool in diagnostics within medical physics, offering substantial potential for early detection of disease, precise diagnosis, and patient care. By harnessing sophisticated machine learning algorithms, AI can process very large amounts of data to uncover correlations that may escape human detection. Figure 2 demonstrates how AI analyzes and segments medical data to produce diagnostic results. These results are then reviewed and refined to support precise decision-making for accurate diagnosis. A key advantage of AI in diagnostics is that it is able to enhance image interpretation and provide more consistent, accurate, and rapid insights. Rajpurkar *et al.* (2018) introduced CheXNet, a deep-learning algorithm capable of detecting pneumonia from

chest X-rays with greater accuracy than practicing radiologists. The study demonstrated that CheXNet could achieve a diagnostic accuracy that surpassed that of practicing radiologists, highlighting AI's potential to enhance clinical decision-making. Topol (2019) provided an extensive overview of AI's role in diagnostics across various fields such as cardiology, radiology, and pathology. The study highlighted how AI could process large volumes of data leading to faster and more accurate diagnoses. In cardiology, for example, AI has been used to analyze electrocardiograms (ECGs) and echocardiograms, detecting abnormalities that may not have been seen by humans.

2.4 Patient Outcomes

Patient outcomes are one of the most significant areas of focus in the integration of technology into healthcare. Patient outcomes refer to the results of healthcare practices, including recovery, quality of life, and survival rates. Studies like those by Jha and Topol (2016) have shown that AI can significantly improve patient outcomes by enabling personalized medicine, improving treatment protocols, and facilitating early disease detection. According to Topol (2019), AI can identify specific mutations in a patient's gene that may influence how they respond to certain medications. This allows clinicians to select treatments that are more effective for that particular patient, thereby eradicating the trial-and-error approach that often characterizes traditional treatment methods.

Additionally, AI can keep track of how patients respond to treatment, adjusting the therapy as needed to ensure the best possible outcome. This dynamic and responsive approach to patient care is crucial to improving recovery rates and overall survivorship outcomes. Obermeyer and Emanuel (2016) discussed the ethical implications involved in the integration of AI into healthcare.

The study emphasized the need for equitable AI deployment across different demographics to ensure patients benefit from AI advancements.

While previous studies have extensively explored the impact of Artificial Intelligence (AI) on specific aspects of medical physics, such as imaging, radiation therapy, treatment planning, or diagnosis, there remains a significant gap in the literature about integrating AI's influence across these domains. Moreover, the collective impact of these advancements on patient outcomes has not been thoroughly examined. This review aims to fill this gap by providing an analysis of AI's transformative role in each of these critical areas, (imaging, treatment planning, and diagnosis) and by highlighting how these innovations converge to enhance patient outcomes. By offering a holistic perspective, this paper contributes to a deeper understanding of AI's potential to improve medical physics and improve overall healthcare delivery.

3.0 Methods

3.1 Search Strategy and Selection Criteria

A comprehensive search was employed to identify studies that are relevant in examining the impact of AI on medical physics. The following databases were searched: PubMed, Web of Science, IEEE Xplore, ResearchGates, Scopus, and Google Scholar. The search was conducted using keywords related to AI and medical physics, including "artificial intelligence," "machine learning," "deep learning," "medical imaging," "treatment planning," "diagnostics," and "patient outcomes." The search was limited to studies published between 2016 and 2024 to ensure that the most recent advancements and research were captured.

After the search, 1,150 articles were obtained. With the removal of duplicate articles, 867 studies remained. These studies were then screened to

extract ones relevant to the review based on their abstracts and keywords. Studies that were not directly related to AI in medical physics or did not meet the inclusion criteria were excluded. This screening process resulted in 30 articles for full-text review as shown in Table 1.

3.2 Inclusion criteria

- Papers published between 2010 and 2024.
- Peer-reviewed articles, conference papers, and review articles.
- Studies focusing on the application of AI in medical imaging, treatment planning, diagnostics, and patient outcomes.
- Articles available in English.

3.3 Exclusion criteria

- Non-peer-reviewed articles and gray literature.
- Studies with insufficient data or unclear methodology.
- Articles not directly related to medical physics or AI.

3.4 Data Extraction

Data extraction was done by two reviewers to ensure accuracy and consistency. Relevant information collected from each study includes the authors, publication year, study method, study aim and purpose, and key findings.

The data were synthesized using a narrative approach, focusing on the impact of AI on medical imaging, treatment planning, diagnostics, and patient outcomes. The synthesis process involved categorizing the studies based on their application areas and summarizing the key findings and implications of each study.

4.0 Results of Review

4.1 Overview of Included Studies

30 studies were included in the final review. These studies were based on four main areas: medical imaging, treatment planning, diagnostics, and patient outcomes, and are shown

in Table 1. The included studies were published between 2016 and 2024, with a significant increase in publications in recent years, reflecting the growing interest and advancements in AI applications in medical physics.

Table 1: Overview of Reviewed Studies

Author/Year	Title	Purpose of study	Method	Result
Zhang, et al. 2024.	Reducing pediatric total-body PET/CT imaging scan time with multimodal artificial intelligence technology.	To decrease the scan time and enhance image quality in pediatric total-body imaging.	Low-dose image fusion. Multimodal image reconstruction.	Multimodal AI techniques can significantly improve PET image quality.
Beckers <i>et al.</i> , 2021	The EU medical device regulation: Implications for artificial intelligence-based medical device software in medical physics.	To guide Medical Physicist Experts on the impact of EU MDR on AI-based medical devices.	Review of regulatory processes and quality management for AI device development.	Adhering to EU MDR ensures safe and effective clinical integration of AI-based devices.
Tomal & Massera. 2021.	Breast glandularity and mean glandular dose assessment using a deep learning framework: Virtual patients study.	To develop a deep learning framework for estimating breast glandularity to improve mean glandular dose (MGD) calculations in mammography.	AI-based models, including XNet and multilayer perceptron architectures, trained on simulated mammography images to predict volume glandular fraction (VGF) for MGD calculation.	The AI models accurately predicted VGF and MGD, closely matching ground truth values, demonstrating the framework's effectiveness for virtual breast phantoms.
Buls <i>et al.</i> , 2021.	Performance of an artificial intelligence tool with real-time clinical workflow integration – detection of intracranial hemorrhage and pulmonary embolism.	To evaluate the performance of a commercial AI tool as a second reader for detecting intracranial hemorrhage (ICH) and pulmonary embolism (PE) in a diverse clinical setting.	Analyzing 500 consecutive non-contrast head CTs and Computed Tomography Pulmonary Angiography (CTPA) scans using the AI tool, with results compared to expert radiologist readings across various clinical conditions.	The AI tool showed good performance in detecting ICH and PE with higher sensitivity, suggesting its potential as a real-time adjunct in radiology workflows.
Diaz <i>et al.</i> , 2021	Data preparation for artificial intelligence in	To provide a comprehensive guide for	Review key steps in medical image preparation, along	Proper image preparation is crucial for

	medical imaging: a comprehensive guide to open-access platforms and tools	preparing medical images for AI algorithm development and application.	with open-access tools and repositories.	reliable AI development, and the paper highlighted available tools and repositories.
Dong & Xing, 2020	Deep DoseNet: a deep neural network for accurate dosimetric transformation between different spatial resolutions and different dose calculation algorithms for precision radiation therapy	To introduce a deep learning strategy for transforming low-cost dose distributions into highly accurate dose plans.	The study used Deep DoseNet to enhance dose distributions calculated by the low-resolution Anisotropic Analytical Algorithm (AAA) to match the high-resolution Acuros XB (AXB) algorithm, training the network on 25,168 dose slices from various patient CT scans. A CNN was trained on a large dataset of 129,450 clinical images covering 2,032 skin diseases, and its performance was compared with that of 21 dermatologists in classifying skin cancer.	The DL-based Deep DoseNet significantly improved dose accuracy and Gamma index passing rates compared to AAA, closely matching AXB results with much faster calculation times.
Esteva <i>et al.</i> , 2017.	Dermatologist-level classification of skin cancer with deep neural networks	To demonstrate the effectiveness of a deep convolutional neural network (CNN) in classifying skin lesions directly from images.	A CNN was trained on a large dataset of 129,450 clinical images covering 2,032 skin diseases, and its performance was compared with that of 21 dermatologists in classifying skin cancer.	The CNN achieved performance comparable to dermatologists in identifying both common and deadly skin cancers.
Fan <i>et al.</i> , 2020.	Data-driven dose calculation algorithm based on deep U-Net	To develop a novel deep learning-based algorithm for fast and accurate dose calculation in radiation therapy.	A 3D U-Net-like deep residual network was trained on CT images from 200 patients to predict 3D dose distributions, with its accuracy evaluated against a treatment planning system (TPS) on an additional 47 patients.	The DL algorithm achieved high accuracy and consistency with TPS calculations, demonstrating its potential to enhance efficiency and accuracy in radiation dose calculation.
Funama <i>et al.</i> , 2021.	Conditional generative adversarial networks to generate pseudo-	'To generate pseudo low monoenergetic CT images from 120-kVp CT images	A cGAN was trained on paired 120-kVp and 55-keV CT images from 48 patients to	The cGAN successfully generated high-quality pseudo-low

	low monoenergetic CT images from a single-tube voltage CT scanner.	using a conditional Generative Adversarial Network (cGAN)'. To develop a deep learning model for predicting dose distributions in 3D-CRT (Conformal Radiation Therapy) for left-sided breast cancer.	generate pseudo 55-keV images, with image quality evaluated across different training epochs.	monoenergetic images with performance metrics improving slightly over training epochs.
Hedden & Xu. 2021	Radiation therapy dose prediction for left-sided breast cancers using two-dimensional and three-dimensional deep learning models	To develop a deep learning model for predicting dose distributions in 3D-CRT (Conformal Radiation Therapy) for left-sided breast cancer.	2D and 3D U-net models were trained and evaluated using patient CT data and organ-at-risk (OAR) masks.	Both models produced clinically acceptable results, with the 3D model performing better.
Huan <i>et al.</i> , 2022.	Meta-optimization for fully automated radiation therapy treatment planning.	To develop a meta-optimization framework, MetaPlanner (MP), to automate radiation therapy treatment planning.	The MP algorithm was trained to use a derivative-free optimization method to adjust hyperparameters, mimicking clinical decision-making by optimizing a meta-scoring function.	MP demonstrated a better performance than manual Volumetric Modulated Arc Therapy (VMAT) planning, leading to a reduced planner workload while improving plan quality.
Huang <i>et al.</i> , 2021	Fully automated noncoplanar radiation therapy treatment planning.	To develop a fully automated noncoplanar (NC) treatment planning method using Pareto optimal projection search (POPS) algorithm to enhance dosimetric quality in radiation therapy.	Noncoplanar-pareto optimal projection search (NC-POPS) was developed to adapt the POPS algorithm for NC beam angle optimization and automate inverse planning, applied in Intensity-Modulated Radiation Therapy (IMRT) and VMAT.	NC-POPS significantly enhanced OAR sparing and achieved better dose conformity and homogeneity compared to traditional coplanar methods, improving both plan quality and planning efficiency.
Zhou <i>et al.</i> 2021.	A Review of Deep Learning in Medical Imaging: Imaging Traits, Technology Trends, Case Studies with Progress Highlights, and	To review the challenges and advancements of deep learning in medical imaging and explore its applications in various clinical scenarios.	Examined emerging deep learning trends addressing medical imaging challenges, alongside case studies in digital pathology and various imaging	The future promise of deep learning in medical imaging involves integrating clinical data to enable personalized

	Future Promises.		fields.	treatment insights and drive new healthcare advancements. Proposed a new approach where an explicit physics prior is included as an additional input into the network architecture, improving medical imaging.
Nemirovsky-Rotman & Bercovich. 2024.	Explicit Physics-Informed Deep Learning for Computer-aided Diagnostic Tasks in Medical Imaging	To review recent work on incorporating physics-based priors into deep learning methods in medical imaging applications.	Review of existing literature on physics-based deep learning in medical imaging and use of perturbed physical priors as part of the training data.	
Jones <i>et al.</i> , 2024	Automation and artificial intelligence in radiation therapy treatment planning.	To explore the impact of AI on radiation therapy planning and future implications for radiation therapists (RTs) in Australia.	Reviewed AI integration in radiation oncology, focusing on radiation therapy roles in adopting and adapting to new technologies.	AI enhances efficiency in radiation therapy planning, with RTs crucial in its implementation.
Liu <i>et al.</i> 2021.	Automatic segmentation of clinical target volume and organs-at-risk for breast conservative radiotherapy using Convolutional Neural Network.	To develop and evaluate a U-ResNet model for fast and consistent auto-segmentation of clinical target volumes (CTV) and OARs in breast cancer radiotherapy.	The U-ResNet model was trained on CT scans from 160 breast cancer patients, with performance assessed using the Dice Similarity Coefficient (DSC) and 95th percentile Hausdorff distance (95HD).	The model achieved high accuracy in auto-segmentation, with no significant differences compared to manual delineations, and reduced segmentation time to 10 seconds.
Litjens <i>et al.</i> 2017	A survey on deep learning in medical image analysis.	To review the application of DL in medical image analysis.	Surveys the use of DL in various medical imaging tasks like classification, detection, segmentation, and registration, across multiple application areas like neuro, retinal, and cardiac imaging.	Highlights how DL has become integral to medical image analysis, identifies challenges in its application, and points out specific contributions that address these challenges.
Ma <i>et al.</i> 2019	Incorporating dosimetric features into the prediction of 3D	To enhance the accuracy of dose prediction in IMRT/VMAT	Developed a CNN using patient contour information and	The new method demonstrated improved prediction

	VMAT dose distributions using deep convolutional neural network.	planning by incorporating both dosimetric and geometric features into a deep learning model.	dose distribution data from Planning Target Volume (PTV)-only plans, trained on 60 VMAT plans, and tested on 10 cases.	accuracy, with the reduced sum of absolute residuals (SARs) for the PTV, bladder, and rectum, outperforming models based solely on geometric features.
Men <i>et al.</i> 2017	Automatic segmentation of the clinical target volume and organs at risk in the planning CT for rectal cancer using deep dilated convolutional neural networks	To develop a ‘deep dilated convolutional neural network’ (DDCNN) for fast and consistent auto-segmentation of clinical target volume (CTV) and OARs in radiotherapy.	Utilized a DDCNN with a multi-scale convolutional architecture and dilated convolutions, trained on 218 rectal cancer patients, validated on 60; segmentation accuracy measured by Dice similarity coefficient (DSC).	DDCNN provides accurate, efficient segmentation, improving consistency and workflow in radiotherapy, and is robust to patient variations.
Men <i>et al.</i> 2017	Deep Deconvolutional Neural Network for Target Segmentation of Nasopharyngeal Cancer in Planning Computed Tomography Images.	To develop a deep deconvolutional neural network (DDNN) for accurate segmentation of nasopharynx gross tumor volume (GTVnx), the metastatic lymph node GTVnd, CTV, and OARs in radiotherapy planning for nasopharyngeal carcinoma.	Developed a DDNN with encoder-decoder architecture, trained on 184 NPC patients, and tested on 46; segmentation accuracy measured using DSC.	DDNN accurately segments GTVnx and CTV, with lower accuracy for GTVnd due to variability; improvement is expected with more data and MR image integration.
Montalt-Tordera <i>et al.</i> 2021.	Machine learning in magnetic resonance imaging: image reconstruction.	To review and summarize current ML approaches in MRI reconstruction.	Overview of machine learning techniques applied in k-space and image-space for MRI reconstruction, comparing their performance and identifying trends.	ML methods showed promise in producing natural-looking images with faster computation, but challenges remain in clinical adoption.
Nguyen <i>et al.</i>	A feasibility study	To streamline	A modified U-net	The model

2019	for predicting optimal radiation therapy dose distributions of prostate cancer patients from patient anatomy using deep learning.	radiation therapy planning by predicting accurate dose distributions from patient contours.	convolutional DL model was utilized to predict dose distributions from PTV and OAR contours in prostate cancer patients.	successfully predicted dose distributions with high accuracy.
Nousiainen <i>et al.</i> 2021	Automating chest radiograph imaging quality control.	To automate quality control of chest radiograph imaging using CNN.	Trained six CNN models on 2,589 chest radiographs, utilizing image augmentation and manual annotations to detect quality features.	The models achieved high accuracy in detecting quality features, aligning well with human annotators.
Obermeyer & Emanuel. 2016.	Predicting the future—big data, machine learning, and clinical medicine.	To explore the role of ML in medicine, and its potential to improve prognosis and decision-making by analyzing complex, large-scale data.	Reviewed how ML algorithms learn from vast datasets, handle numerous variables, and predict outcomes, with examples from ongoing research and other scientific fields.	ML enhances medical prognosis and decision-making, but it requires careful attention to data quality and model validation.
Papadimitroulas <i>et al.</i> 2021.	Artificial intelligence: deep learning in oncological radiomics and challenges of interpretability and data harmonization.	To review the use of Deep Neural Networks (DNN) in radiomics and their potential for developing explainable AI in clinical practice.	The study examines DNNs for image analysis, radiomics feature extraction, and interpretability methods.	DNNs enhance radiomics and explainable AI, but broader data sets are required for more robust and clinically valuable models.
Rajpurkar <i>et al.</i> 2018	Deep learning for chest radiograph diagnosis: A retrospective comparison of the CheXNeXt algorithm to practicing radiologists	To evaluate the performance of a DL algorithm, CheXNeXt, in detecting thoracic pathologies in chest radiographs compared to radiologists.	A CNN, CheXNeXt was trained on the ChestX-ray8 dataset and validated against a panel of radiologists.	CheXNeXt achieved radiologist-level performance in detecting 11 out of 14 pathologies, with faster interpretation times, but underperformed in diagnosing cardiomegaly, emphysema, and hiatal hernia.
Ricciardi <i>et al.</i> 2021.	A deep learning classifier for digital breast	To create a DL system for automatically	Three DCNN architectures (AlexNet, VGG19,	The DBT-DCNN achieved high accuracy (90%),

	tomosynthesis	classifying the presence or absence of mass lesions in digital breast tomosynthesis (DBT) exams.	and DBT-DCNN) were compared using image-level DBT slice classification on datasets from two hospitals, with performance evaluated via accuracy, sensitivity, and area-under-the-curve (AUC) metrics.	sensitivity (96%), and AUC (0.89), with Grad-CAM effectively highlighting tumor regions in the images.
Ritz <i>et al.</i> 2021.	Meniscal lesion detection and characterization in adult knee MRI: a deep learning model approach with external validation	To evaluate a DL model for detecting meniscal tears and identifying the presence of migrated meniscal fragments.	A large annotated knee MRI database was used to train and validate DL models, with performance compared to radiologist reports.	The DL algorithm achieved high AUC values (up to 0.95) for meniscal tear detection and migration characterization, with strong external validation results.
Gullo <i>et al.</i> 2024.	Artificial Intelligence-Enhanced Breast MRI Applications in Breast Cancer Primary Treatment Response Assessment and Prediction	To provide an overview of AI applications in MRI for evaluating and predicting response to primary systemic therapy (PST) in breast cancer, along with the challenges of these techniques in clinical practice.	Review literature on AI-enhanced MRI, covering classical ML and DL methods, to assess their effectiveness in predicting PST response before and during treatment.	AI-enhanced MRI improves prognostication, enabling treatment de-escalation, and reducing surgical delays.
Zhou <i>et al.</i> 2022.	Development of a deep learning-based patient-specific target contour prediction model for markerless tumor positioning.	To develop a markerless DL-based method for real-time pancreatic tumor tracking during radiation therapy using Kilovolt (Kv) X-ray imaging systems.	A DL model was fine-tuned with augmented digitally reconstructed radiograph (DRR) images from 14 patients, with performance evaluated using Dice similarity coefficients (DSC) and 3D positioning errors.	The model achieved high positioning accuracy, demonstrating its potential for real-time tumor tracking without markers.

5.0 Discussion

The finding of this review shows that AI can improve various domains of medical physics. AI has demonstrated advancements, in the area of medical imaging, where it has vastly improved image quality and diagnostic accuracy (Zhou *et al.*, 2021). ‘Studies have shown that AI can better predict radiation-induced toxicity than traditional methods, aiding clinical decision-making’ (Huang *et al.*, 2021; Huang *et al.*, 2022). The integration of AI in radiation therapy shows progress in optimizing treatment planning and delivery.

Beyond the technical improvements, the ethical implications of AI integration into healthcare cannot be overlooked and must be considered. Obermeyer and Emanuel (2016) and Morley *et al.* (2020) provide a comprehensive overview of these ethical considerations. These considerations are crucial for developing governance frameworks that can guide the successful integration of AI in medical physics (Reddy *et al.*, 2019). The use of AI to personalize treatment offers another layer of precision in patient care. Shickel *et al.* (2018) highlight how deep learning techniques are revolutionizing the analysis of electronic health records, enabling more tailored and effective treatment plans. Overall, while AI offers immense potential to revolutionize medical physics, future research and clinical applications must consider these broader implications to ensure that advancements in technology translate into equitable and ethical improvements in patient care.

5.1 Impact of AI on Medical Imaging

AI has significantly enhanced the quality and accuracy of medical imaging. Recent studies have shown that AI algorithms are significantly superior to human experts to a large extent in image interpretation.

- **Skin Cancer Classification:** Esteva *et al.* (2017) showed that "a deep-learning algorithm could classify skin cancer with accuracy comparable to that of dermatologists". The algorithm analyzed dermoscopic images and achieved high sensitivity and specificity, highlighting AI's potential in dermatology.
- **Breast Cancer Screening:** AI systems can improve the accuracy of breast cancer screening programs. According to McKinney *et al.* (2020), ‘AI systems outperformed radiologists in identifying breast cancer in mammograms’. Ricciardi *et al.* (2021) in their work showed the use of deep learning classifiers in digital breast tomosynthesis (DBT). They highlighted that AI could enhance diagnostic accuracy in breast cancer screening and reduce radiologist workload. The work done by Tomal and Massera (2021) presented a deep learning framework to assess ‘breast glandularity and mean glandular dose using virtual patients’. Their study reveals that the deep learning approach can accurately predict glandular tissue distribution and dose, offering a promising tool for personalized breast cancer screening and radiation dose optimization.
- **Medical Image Analysis:** The review by Litjens *et al.* (2017) on the use of ‘deep learning in medical imaging analyses found that DL techniques improved the accuracy and efficiency of image analysis. Additionally, according to Nemirovsky-Rotman & Bercovich. (2024), ‘integrating physics-based priors into deep learning models significantly improves the models' stability and generalization in medical imaging,

making them more reliable for critical applications’.

- **CT and Applications:** Buls *et al.* (2021) assessed an FDA (Food and Drug Administration)-approved AI tool for diagnosing ‘intracranial hemorrhage (ICH) and pulmonary embolism (PE)’ with high accuracy, demonstrating AI’s potential in enhancing diagnostic capabilities in CT imaging. Furthermore, Zhang *et al.* (2024) in their work introduced a three-dimensional (3D) neural network that integrates ‘low-dose CT’ images to enhance the quality of pediatric CT images from ultrashort scans. This approach improved image quality by effectively fusing anatomical and functional information.
- **MRI Applications:** Montalt-Tordera *et al.* (2021) reviewed AI applications in MRI reconstruction, highlighting machine learning approaches that enhance image quality and speed up the inherently slow MRI acquisition process. Zegers *et al.* (2021) discussed AI’s potential in neuro-oncology, emphasizing applications in synthetic CT generation, auto-segmentation, and outcome prediction.

5.2. Impact of AI on Treatment Planning

AI has introduced more personalized and precise approaches to treatment planning, especially in radiation therapy. AI-driven systems optimize treatment plans by analyzing patient data and predicting responses to different treatment options.

- **Radiotherapy Treatment Planning:** Nguyen *et al.* (2019) emphasized that AI-driven systems could improve dosimetry in radiotherapy, enhancing the precision and effectiveness of radiation delivery.

The study highlighted improvements in dose distribution and reduced treatment times. Also, Jones *et al.* (2024) highlighted the critical role of AI in advancing personalized and high-quality treatment planning in radiation therapy.

- **Proton Therapy Planning:** Boldrini *et al.* (2020) reviewed AI applications in optimizing treatment plans for proton therapy. The study demonstrated that AI could enhance dose distribution and reduce treatment times, improving the overall efficacy of proton therapy.
- **Dose Prediction for Breast Cancer:** Hedden *et al.* (2021) investigated deep learning applications in predicting optimal dose distribution for breast cancer radiotherapy, using modified U-net architectures to generate reference dose maps for automatic plan generation. Gullo *et al.* (2024) provided an overview of ML and DL applications in MRI for breast cancer treatment. They believed that AI-enhanced MRI improved the treatment process.
- **Quality Assurance:** Nousiainen *et al.* (2021) focused on automating quality control (QC) in chest radiograph imaging. They developed and validated an automated QC tool that significantly improves the efficiency and consistency of image quality assessments. The tool demonstrated strong agreement with manual quality control methods, suggesting that it could enhance clinical workflows by reducing the time and variability associated with manual image quality checks.

5.3. Impact of AI on Diagnostics

Studies have visibly shown that AI can enhance diagnostic accuracy and predictive analytics. AI-

driven diagnostic tools can process large amounts of data to identify items that may be missed by human observers.

- **Pneumonia Detection:** Rajpurkar *et al.* (2018), in their work, introduced CheXNet, an algorithm capable of detecting pneumonia from chest X-rays with greater accuracy than practicing radiologists. The study showed that AI can enhance accuracy in diagnosis and improve treatment outcomes.
- **AI in Diagnostics:** Topol (2019) discussed AI's applications in cardiology, radiology, and pathology, emphasizing that the use of AI leads to faster and more accurate diagnoses, improving patient outcomes. Additionally, Avanzo *et al.* (2021) highlight that AI-driven methodologies are predominantly utilized for diagnostic imaging tasks, particularly in the areas of image classification and segmentation.
- **MRI for Meniscal Tears:** Ritz *et al.* (2021) evaluated AI models used for detecting and characterizing meniscal tears in knee MRI, achieving high performance and demonstrating AI's potential in enhancing diagnostic accuracy in musculoskeletal imaging. Additionally, Men *et al.* (2017) and Liu *et al.* (2021) in their respective works found that AI algorithms are capable of improving the accuracy of segmentation and auto-contouring in radiotherapy, thereby improving diagnostic processes.

5.4. Impact of AI on Patient Outcomes

AI's impact on patient outcomes is profound, with studies showing significant improvements in healthcare delivery and efficiency.

- **Personalized Medicine:** AI provides the appropriate base for a more personalized medicine. Jha and Topol (2016) highlighted AI's role in enabling personalized medicine, optimizing treatment protocols, and facilitating early disease detection. The study emphasized AI's ability to transform healthcare delivery and enhance patient care.
- **Ethical Considerations:** Obermeyer and Emanuel (2016) discussed the ethical implications involved in the integration of AI into healthcare. The study emphasized the need for equitable AI deployment across different demographics to ensure that all patients benefit from AI advancements.
- Papadimitroulas *et al.* (2021) stated that AI can be used to extract image biomarkers from medical images (radiomics), thus improving patient outcomes. Ma *et al.* (2019) believed 'that AI facilitates the discovery of new biomarkers by analyzing large datasets, advancing radiomics in cancer treatment'.

6.0 Strengths and Limitations of the Review

6.1 Strengths

- The review provides a comprehensive insight into the impact of AI on medical physics, covering key areas such as medical imaging, treatment planning, diagnostics, and patient outcomes.
- A systematic approach was used to identify and analyze relevant studies, ensuring the inclusion of high-quality and relevant literature.
- The review highlights both the benefits as well as challenges associated with AI in medical physics, providing a balanced perspective.

6.2 Limitations

- The review is limited to studies published between 2016 and 2024, which may exclude some relevant earlier studies.
- Only peer-reviewed articles, conference papers, and review articles were included, potentially excluding relevant grey literature.
- The review utilized available studies, whose findings may be subject to publication bias.

7.0 Implications for Clinical Practice and Future Research

The findings of this review have important implications for practice and future research.

- **Clinical Practice:** The integration of AI into medical physics can enhance diagnostic accuracy, treatment planning, and patient outcomes. Healthcare practitioners should consider incorporating AI-driven tools and systems into their practice to improve patient care. However, it is essential to address challenges involving data privacy and the implementation of standardized protocols to ensure the ethical and effective use of AI technologies.
- **Future Research:** There is a need for further research to assess the limitations associated with AI in medical physics. Future studies should focus on developing standardized protocols, to ensure data privacy. Additionally, research should explore the ethical implications of AI deployment and its impact on different demographic groups to ensure equitable access to AI-driven healthcare advancements.

8.0 Recommendations

1. Develop and Enforce Standardized Protocols for AI Implementation:

Governments and regulatory bodies should prioritize the development and enforcement of standardized protocols for the implementation of AI in medical physics. These protocols should cover data privacy, ethical considerations, and safety standards in the use of AI in healthcare.

2. **Invest in AI Education and Training Programs for Medical Physicists:** Medical physicists need specialized education and training. Governments, academic institutions, and professional organizations should collaborate to create comprehensive AI curricula and certification programs that equip medical physicists with the necessary skills to integrate AI into clinical practice.
3. **Promote Research and Development in AI Applications:** Stakeholders, including governments, should increase funding and support for research and development in AI applications within medical physics. This includes encouraging cross-disciplinary collaborations between AI researchers, medical physicists, and clinicians to drive innovation and address existing challenges such as algorithm bias and data scarcity.
4. **Facilitate Access to Large, Diverse Medical Datasets:** A major challenge in AI research is the lack of large, diverse datasets. Governments and healthcare organizations should create and maintain repositories of de-identified patient data that are accessible to researchers. These datasets should be standardized to ensure they are suitable for training AI models, thus enhancing the generalizability and robustness of AI applications.
5. **Ensure Ethical and Equitable AI Deployment:** AI deployment in healthcare must be ethical and equitable. Governments, regulatory bodies, and healthcare

organizations should establish frameworks that ensure AI tools are designed and implemented in ways that do not exacerbate existing health disparities. This includes conducting thorough evaluations of AI systems to prevent bias and ensure that AI benefits all patient populations equally.

6. **Establish Continuous Quality Assurance and Monitoring Systems:** AI systems in medical physics require continuous monitoring and quality assurance to maintain their efficacy and safety. Stakeholders should implement robust quality assurance programs that regularly assess AI tools' performance, especially as they evolve with self-learning capabilities. This will help mitigate risks associated with AI errors and ensure ongoing compliance with regulatory standards.
7. **Encourage Public-Private Partnerships for AI Innovation:** Governments should encourage public-private partnerships to enhance the development and deployment of AI in medical physics. By fostering collaborations between government agencies, academic institutions, healthcare providers, and private industry, stakeholders can pool resources and expertise to overcome technical and financial barriers.
8. When implementing AI-based solutions in healthcare, medical physicists must prioritize rigorous validation of these tools to ensure their reliability and effectiveness. This involves comprehensive testing against established standards and real-world clinical scenarios to confirm that AI tools perform accurately under diverse conditions as stated by Bosmans *et al.* (2021) and Beckers *et al.* (2021).

9.0 Conclusion

This review highlights the transformative potential of AI in medical physics, demonstrating significant advancements in medical imaging, treatment planning, diagnostics, and patient outcomes. AI algorithms have shown remarkable accuracy and efficiency in image interpretation, treatment optimization, and diagnostic processes, leading to improved healthcare delivery and patient care. However, there are challenges such as data privacy concerns and implementation of standardized protocols which have to be addressed to fully harness the benefits of AI in this field. Continued research is important to further explore AI's capabilities and ensure its ethical and equitable deployment in medical physics.

Conflict-of-Interest Disclosure

The authors declare that there were no conflicts of interest regarding the publication of this article.

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