https://jsras.rcc.edu.ly/
Vol.3 No.0 (2026), 304-321
Article history:
Received: 10/6/2026
Accepted: 18/7/2026
Published: 10/9/2026

Journal of Sustainable Research in Applied Sciences

Modern Applications of Artificial Intelligence in Medical Physics: A Theoretical Review

Maha Mansour Aljali[1], Mustafa Ahmed Ben Hkoma[2]
[1] Department of Physics, Faculty of Science, University of Benghazi, Benghazi, Libya
https://orcid.org/0009-0000-607407315
[2]Sustainable Development Research Center
https://orcid.org/0009-0006-6814-8468

DOI https://doi.org/10.36602/jsras.2026.3.2.27
* Maha Mansour Aljali

Index Terms

Artificial Intelligence; Medical Physics; Deep Learning; Medical Imaging; Radiation Therapy; Quality Assurance; Patient Safety; Clinically Trustworthy AI

Abstract

The rapid integration of artificial intelligence (AI) into medical physics is reshaping major applications in medical imaging, radiation therapy, treatment planning, quality assurance, and precision medicine. This study aimed to critically review and analyze contemporary AI applications in medical physics, evaluate their technical and clinical contributions, identify the major barriers limiting their transition from experimental performance to safe clinical implementation, and highlight emerging directions for future research. A descriptive, comparative, analytical, and critical review approach was adopted to synthesize recent scientific literature and critically compare previous studies in terms of technological maturity, generalizability, data quality, external validation, interpretability, quality assurance, and patient-safety implications. The findings indicate that the most mature AI applications are concentrated in medical image analysis and reconstruction, automatic segmentation, tumor and organ-at-risk delineation, radiotherapy treatment planning, dose prediction, and quality assurance. AI has demonstrated considerable potential to reduce workflow time, improve consistency and accuracy, and support adaptive radiotherapy and personalized medicine. However, the critical synthesis revealed a substantial gap between high algorithmic performance and actual clinical readiness**.** Many models continue to rely on retrospective or single-institution datasets, with limited external validation and considerable variability across devices, patient populations, imaging protocols, and clinical environments. Additional concerns include algorithmic bias, uncertainty, limited interpretability, data privacy, cybersecurity, and regulatory accountability. The study concludes that computational accuracy alone is insufficient to establish the clinical value of AI in medical physics and proposes a conceptual transition from an AI accuracy-centered paradigm toward clinically trustworthy AI**.** Within this framework, clinical readiness results from the combined effects of algorithmic performance, representative data quality, external validation, interpretability, uncertainty quantification, professional oversight, workflow integration, regulatory compliance, and patient safety. The study further emphasizes that AI should augment rather than replace medical physicists, supporting a human–AI collaboration model in which professional expertise, verification, and clinical accountability remain central to safe implementation

التطبيقات الحديثة للذكاء الاصطناعي في الفيزياء الطبية: مراجعة نظرية

مها منصور الجالي [1]*، مصطفى أحمد بن حكومة [2]
[1] قسم الفيزياء، كلية العلوم، جامعة بنغازي، بنغازي، ليبيا
[2] مركز أبحاث التنمية المستدامة m_hkoma2017@yahoo.com
https://orcid.org/0009-0006-6814-8468
DOI https://doi.org/10.36602/jsras.2026.3.2.27
* مها منصور الجالي

الكلمات المفتاحية:

الذكاء الاصطناعي؛ الفيزياء الطبية؛ التعلم العميق؛ التصوير الطبي؛ العلاج الإشعاعي؛ ضمان الجودة؛ سلامة المرضى؛ الذكاء الاصطناعي الموثوق سريريًا

الملخص

يشهد توظيف الذكاء الاصطناعي في الفيزياء الطبية تطورًا متسارعًا أسهم في إعادة تشكيل العديد من التطبيقات المرتبطة بالتصوير الطبي، والعلاج الإشعاعي، وتخطيط العلاج، وضمان الجودة، والطب الدقيق. هدفت هذه الدراسة إلى مراجعة وتحليل التطبيقات الحديثة للذكاء الاصطناعي في الفيزياء الطبية، وتقييم إسهاماتها السريرية والتقنية، والكشف عن أهم التحديات والقيود التي تحد من انتقالها من الأداء التجريبي إلى التطبيق السريري الآمن، إلى جانب تحديد الاتجاهات المستقبلية للبحث والتطوير. واعتمدت الدراسة المنهج الوصفي المقارن التحليلي النقدي من خلال مراجعة الأدبيات العلمية الحديثة، ومقارنة نتائج الدراسات السابقة وتحليلها ونقدها من حيث مستوى النضج التقني،

الملخص

وقابلية التعميم، وجودة البيانات، والتحقق الخارجي، وقابلية التفسير، وضمان الجودة وسلامة المرضى. وأظهرت النتائج أن أكثر تطبيقات الذكاء الاصطناعي نضجًا تتركز في تحليل الصور الطبية، وإعادة بنائها وتحسينها، والتجزئة الآلية، وتحديد الأورام والأعضاء المعرضة للخطر، وتخطيط العلاج الإشعاعي، والتنبؤ بالجرعات، وضمان الجودة. كما بينت الدراسة أن الذكاء الاصطناعي يمتلك قدرة واضحة على تقليل الزمن التشغيلي، وتحسين الاتساق والدقة، ودعم العلاج الإشعاعي التكيفي والطب الشخصي. إلا أن التحليل النقدي كشف عن فجوة مهمة بين ارتفاع الأداء الخوارزمي والاستعداد السريري الفعلي؛ إذ تعتمد العديد من النماذج على بيانات استعادية أو أحادية المركز، مع محدودية التحقق الخارجي وتباين الأجهزة والسكان والبروتوكولات، فضلًا عن تحديات التحيز الخوارزمي، وعدم اليقين، وقابلية التفسير، والخصوصية، والأمن السيبراني، والمسؤولية التنظيمية. وتخلص الدراسة إلى أن الدقة الحسابية وحدها لا تكفي للحكم على نجاح الذكاء الاصطناعي في الفيزياء الطبية، وتقترح الانتقال من نموذج قائم على دقة الذكاء الاصطناعي إلى إطار أوسع يقوم على الذكاء الاصطناعي الموثوق سريريًا، الذي يجمع بين الأداء الخوارزمي، وجودة البيانات، والتحقق الخارجي، وقابلية التفسير، وتقدير عدم اليقين، والإشراف المهني، والتكامل السريري، وسلامة المريض. كما تؤكد الدراسة أن الذكاء الاصطناعي ينبغي أن يعمل على تعزيز خبرة الفيزيائي الطبي لا استبدالها، ضمن نموذج تعاون بين الإنسان والذكاء الاصطناعي يحافظ على المسؤولية المهنية والرقابة السريرية

الكلمات المفتاحية:

1. Introduction

Artificial Intelligence (AI) has emerged as one of the most transformative technologies in modern healthcare, fundamentally reshaping the way medical data are analyzed, interpreted, and utilized in clinical decision-making. Over the last decade, rapid advances in machine learning, deep learning, and computer vision have enabled healthcare systems to process large volumes of medical information with unprecedented speed and accuracy. Among the healthcare disciplines experiencing significant transformation, medical physics has become one of the most promising fields for AI integration because of its reliance on quantitative imaging, radiation measurement, computational modeling, and precision treatment planning (Topol, 2019; Hosny et al., 2018). Medical physics plays a central role in diagnostic imaging, radiation therapy, nuclear medicine, and radiation protection by ensuring that physical principles are effectively translated into safe and accurate clinical practice. Traditionally, medical physicists have depended on mathematical modeling, manual quality assurance procedures, and expert interpretation to optimize imaging systems and radiation treatments. However, the increasing complexity of modern imaging modalities and radiotherapy technologies has generated massive datasets that exceed the capacity of conventional analytical approaches. Consequently, AI has become an essential tool for supporting medical physicists in data analysis, automation, and clinical optimization (Thompson et al., 2020).

One of the most influential applications of AI in medical physics is medical image analysis. Deep learning algorithms have demonstrated remarkable capabilities in automated image segmentation, lesion detection, tissue characterization, and image reconstruction across computed tomography (CT), magnetic resonance imaging (MRI), positron emission tomography (PET), and ultrasound imaging. These capabilities reduce observer variability while improving diagnostic consistency and efficiency. Furthermore, AI-based image enhancement techniques allow high-quality image reconstruction from lower radiation doses, contributing directly to patient safety without compromising diagnostic performance (Pesapane et al., 2020).

Beyond treatment planning, AI contributes significantly to quality assurance (QA) in medical physics. Conventional QA procedures require considerable time and human expertise to verify the performance of imaging equipment and radiation delivery systems. Machine learning models are increasingly being used to detect equipment anomalies, predict machine failures, identify dosimetric deviations, and automate routine quality control tasks. Predictive maintenance supported by AI not only enhances operational efficiency but also improves patient safety by reducing the likelihood of technical errors before they occur during clinical practice (Thompson et al., 2020).

Artificial intelligence is also accelerating the transition toward precision medicine. By integrating imaging biomarkers, radiation dosimetry, genomic information, and electronic health records, AI enables predictive models capable of estimating treatment response, toxicity risk, and long-term clinical outcomes. Such integration supports individualized treatment strategies rather than standardized protocols, allowing medical physicists and clinicians to tailor radiation therapy according to each patient's biological and anatomical characteristics (Lambin et al., 2021).

Despite these remarkable achievements, the implementation of AI in medical physics is accompanied by several scientific and practical challenges. The reliability of AI systems depends heavily on the quality, diversity, and representativeness of training datasets. Limited data availability, algorithmic bias, insufficient external validation, and the "black-box" nature of many deep learning models remain significant concerns. Furthermore, ethical issues related to patient privacy, data security, algorithm transparency, and regulatory approval continue to influence the clinical adoption of AI-based technologies (Topol, 2019).

Another important consideration is that AI is not intended to replace medical physicists but rather to augment their expertise. Successful implementation requires close collaboration between medical physicists, radiation oncologists, radiologists, computer scientists, and software engineers. Medical physicists remain responsible for validating AI algorithms, ensuring their clinical safety, interpreting algorithm outputs, and maintaining regulatory compliance. Therefore, AI should be viewed as a decision-support technology that enhances professional performance rather than substituting expert judgment (Pesapane et al., 2020).

The rapid evolution of generative AI, foundation models, explainable AI (XAI), federated learning, and multimodal deep learning is expected to further transform medical physics during the coming years. These emerging technologies promise greater automation, improved generalizability, enhanced interpretability, and secure collaborative learning across healthcare institutions without compromising patient confidentiality. Their integration may redefine future workflows in diagnostic imaging, radiation therapy planning, adaptive treatment, and clinical quality management (Lambin et al., 2021).

Given these developments, reviewing contemporary AI applications in medical physics has become increasingly important for understanding current technological advances, identifying implementation challenges, and highlighting future research opportunities. Accordingly, this theoretical review aims to examine the modern applications of artificial intelligence in medical physics, discuss their contributions to diagnostic imaging and radiation therapy, evaluate current limitations, and explore future directions that may support safer, more accurate, and more personalized healthcare delivery

2 . Research Problem

The rapid advancement of artificial intelligence (AI) has significantly transformed healthcare by improving medical imaging, radiation therapy, and clinical decision-making. In the field of medical physics, AI has demonstrated considerable potential to enhance diagnostic accuracy, optimize treatment planning, automate quality assurance, and support precision medicine. Despite these advancements, there remains a need for a comprehensive theoretical review that systematically examines modern AI applications in medical physics, identifies their current contributions, discusses the challenges limiting their clinical implementation, and explores future research directions. Therefore, this study seeks to provide an up-to-date theoretical overview of the role of artificial intelligence in advancing medical physics and improving healthcare delivery.

Research Questions

1. What are the most recent applications of artificial intelligence in medical physics?
2. How does artificial intelligence contribute to improving medical imaging and radiation therapy?
3. What are the major technical, ethical, and regulatory challenges associated with AI implementation in medical physics?
4. How does artificial intelligence enhance quality assurance and patient safety in medical physics?
5. What are the future trends and research opportunities for artificial intelligence in medical physics?

3. Significance of the Study

T The significance of this study lies in its critical and integrative assessment of artificial intelligence in medical physics beyond conventional measures of algorithmic accuracy. While previous research has extensively documented the technical performance of AI in medical imaging, automated segmentation, radiotherapy treatment planning, dose prediction, quality assurance, and precision medicine, evidence regarding its actual clinical readiness remains fragmented. Therefore, this review is important because it brings these applications together within a unified analytical perspective that evaluates not only what AI can technically achieve, but also the conditions under which these achievements can be translated into safe, reliable, generalizable, and clinically meaningful practice. In particular, the study critically examines the relationship between algorithmic performance, data quality and representativeness, external validation, interpretability, uncertainty quantification, workflow integration, regulatory requirements, professional oversight, and patient safety. This multidimensional perspective is especially relevant to medical physics, where even technically small algorithmic errors may have significant consequences for image interpretation, dose calculation, treatment planning, or radiation delivery. The study also has professional significance by emphasizing the evolving role of the medical physicist as a validator, supervisor, risk assessor, and clinical governor of AI-assisted systems rather than a professional replaced by automation. Moreover, by highlighting limitations in external validation and the geographical imbalance of current evidence, particularly the limited representation of African and resource-constrained healthcare environments, the review provides a basis for identifying context-sensitive research priorities and implementation requirements. Accordingly, the study contributes to the literature by supporting a conceptual transition from an accuracy-centered AI paradigm to a clinically trustworthy AI paradigm, in which successful implementation is judged by the combined achievement of technical performance, robustness, transparency, clinical utility, patient safety, and accountable human–AI collaboration. This perspective provides a stronger evidence-based foundation for future research, clinical implementation, professional training, quality assurance, and regulatory decision-making in AI-enabled medical physics.

4 . Objectives of the Study

The study aims to:

1. Review and synthesize the contemporary scientific literature on modern applications of artificial intelligence in medical physics.
2. Analyze the role of artificial intelligence in improving medical imaging, radiation therapy, quality assurance, and precision medicine.
3. Critically evaluate the opportunities, limitations, and challenges associated with implementing AI technologies in medical physics.
4. Compare recent research findings to identify common trends, research gaps, and areas of disagreement in the existing literature.
5. Propose future research directions and practical recommendations that support the effective integration of artificial intelligence into medical physics research and clinical practice.

5 .Theoretical Framework

❖ Artificial Intelligence in Medical Physics

Artificial Intelligence (AI) represents a broad family of computational approaches designed to perform tasks that traditionally require human intelligence, including pattern recognition, prediction, classification, optimization, and decision support. Within healthcare, the most influential AI approaches include machine learning (ML), deep learning (DL), computer vision, and increasingly generative and multimodal AI models. Their importance in medical physics arises from the highly quantitative and data-intensive nature of the discipline, where clinical decisions frequently depend on complex imaging datasets, radiation measurements, computational models, and treatment-planning parameters (Topol, 2019; Hosny et al., 2018).

Medical physics provides an especially suitable environment for AI because it connects physical measurement with clinical decision-making. Medical physicists are involved in diagnostic imaging, radiation therapy, nuclear medicine, dosimetry, radiation protection, equipment calibration, and quality assurance. Traditionally, many of these activities have relied on mathematical models, manual verification, predefined algorithms, and professional judgment. However, the increasing complexity and volume of medical data have created conditions in which conventional analytical methods may become inefficient, providing a strong rationale for AI-assisted analysis and automation. This relationship between AI and the quantitative foundations of medical physics forms the conceptual basis of the present review.

❖ . Machine Learning and Deep Learning in Medical Physics

Machine learning enables computational systems to identify relationships within data and generate predictions or classifications without relying exclusively on explicitly programmed rules. Deep learning represents a more advanced subset of ML based on multilayer neural networks capable of learning complex representations from large datasets. In medical physics, these techniques are particularly valuable because medical images and radiation-related datasets often contain multidimensional patterns that may be difficult to characterize through conventional statistical approaches.

Deep learning has therefore become particularly influential in medical imaging, where convolutional and related neural-network architectures can perform image classification, segmentation, reconstruction, detection, and quantitative feature extraction. The growing application of these approaches has shifted AI from being primarily an experimental analytical tool toward becoming a potential component of clinical workflows (Hosny et al., 2018; Pesapane et al., 2020).

❖ . AI in Medical Imaging

Medical imaging constitutes one of the most mature areas of AI application in medical physics. Modern imaging modalities—including Computed Tomography (CT), Magnetic Resonance Imaging (MRI), Positron Emission Tomography (PET), and ultrasound—generate large quantities of complex information that require reconstruction, processing, interpretation, and quality assessment.

AI algorithms can contribute to automated segmentation, lesion detection, tissue characterization, image reconstruction, noise reduction, and image enhancement. Importantly, the potential benefit extends beyond automation. AI-assisted reconstruction may allow diagnostically useful images to be produced from lower-dose acquisitions, thereby linking computational performance directly to the medical-physics principle of radiation-dose optimization. AI may consequently contribute simultaneously to image quality, workflow efficiency, diagnostic consistency, and patient safety (Pesapane et al., 2020). These applications are already central to the study's conceptualization of AI in medical physics.

❖ . AI in Radiation Oncology and Treatment Planning

Radiation oncology represents another major interface between AI and medical physics. Effective radiotherapy requires accurate target delineation, identification of organs at risk, dose calculation, treatment optimization, verification, and adaptation to anatomical changes.

AI-based methods can automate or support several of these functions. Deep learning can assist in organ and tumor segmentation, while predictive models can contribute to dose-distribution estimation and treatment-plan optimization. AI may also support adaptive radiotherapy by processing imaging information acquired during treatment and identifying anatomical changes requiring plan modification (Boldrini et al., 2020).

The theoretical significance of AI in this context is therefore not limited to reducing treatment-planning time. Its greater potential lies in improving the relationship between treatment precision and normal-tissue protection**.** Nevertheless, automated recommendations must remain subject to clinical and physics-based verification because

algorithmic accuracy alone does not establish treatment safety

❖ AI-Based Quality Assurance and Patient Safety

Quality Assurance (QA) is a fundamental responsibility within medical physics because the accuracy and reliability of imaging and radiation-delivery equipment directly affect patient outcomes. Conventional QA procedures frequently require repeated measurements, predefined tolerance tests, equipment inspections, and specialist interpretation.

Machine-learning models provide an opportunity to move some QA activities from predominantly reactive detection toward predictive quality management**.** AI can analyze historical and real-time equipment data to identify abnormal behavior, detect dosimetric deviations, predict equipment failures, and prioritize maintenance activities. Predictive maintenance may therefore reduce unplanned downtime while identifying potential technical failures before they affect clinical procedures (Thompson et al., 2020).

However, this represents an area where human oversight remains indispensable. False-negative predictions could create safety risks, while false-positive alerts could generate unnecessary interventions. AI-based QA should consequently be conceptualized as a decision-support layer complementing established physics-based QA procedures**,** rather than as an unconditional replacement for them.

❖ AI, Radiomics, and Precision Medicine

A further theoretical dimension concerns the transition from standardized treatment protocols toward precision and personalized medicine. AI can integrate multiple sources of information, including medical imaging, radiation dosimetry, clinical records, imaging biomarkers, and potentially genomic information, to identify relationships that may predict treatment response, toxicity, or disease progression.

Radiomics is particularly relevant because it transforms medical images into quantitative features that can subsequently be incorporated into predictive models. Combined with AI, these features may support patient-specific risk stratification and treatment-response prediction. Thus, the role of medical physics can extend beyond optimizing physical dose delivery toward supporting data-driven personalization of treatment (Lambin et al., 2021). The source paper explicitly identifies this integration of imaging biomarkers, dosimetry, genomic information, and electronic health records as a pathway toward individualized treatment.

❖ Challenges and Limitations of AI in Medical Physics

Despite its potential, AI implementation in medical physics presents significant technical, clinical, ethical, and regulatory challenges**.** One of the most important concerns is data dependency. AI models are strongly influenced by the size, quality, diversity, and representativeness of their training datasets. A model developed using data from one institution, imaging device, or patient population may not achieve equivalent performance in another clinical environment.

Algorithmic bias, limited external validation, and the black-box problem associated with many deep-learning models also challenge clinical trust and accountability. Additional concerns include patient privacy, cybersecurity, data governance, transparency, regulatory approval, and responsibility when AI-generated recommendations contribute to clinical errors (Topol, 2019). These limitations are explicitly recognized in the study as important barriers to clinical adoption.

Accordingly, the theoretical framework should reject a purely technology-centered assumption that greater algorithmic accuracy automatically produces better healthcare. The clinical value of AI depends on the interaction between algorithm performance, data quality, external validation, interpretability, professional oversight, workflow integration, and patient safety**.**

❖ . Human–AI Collaboration and the Role of the Medical Physicist

A central principle underlying this review is that AI should be understood primarily as a mechanism for augmenting rather than replacing professional expertise**.** Medical physicists remain responsible for verifying algorithms, evaluating their clinical validity, interpreting outputs, ensuring radiation safety, monitoring quality, and maintaining regulatory compliance. Effective implementation therefore requires multidisciplinary collaboration among medical physicists, physicians, radiologists, radiation oncologists, computer scientists, engineers, and software specialists.

This perspective leads to a human-centered conceptual relationship:

Medical Physics Expertise + AI Capabilities → Augmented Clinical Decision-Making → Improved Accuracy and Efficiency → Enhanced Patient Safety and Personalized Care

Thus, successful AI integration should be evaluated not merely according to whether an algorithm outperforms a human on an isolated computational task, but according to whether human–AI collaboration improves the safety, reproducibility, efficiency, and clinical value of the complete medical-physics workflow**.**

❖ . Emerging AI Technologies and Future Medical Physics

The theoretical framework must also recognize that AI in medical physics is rapidly evolving. Explainable AI (XAI), federated learning, generative AI, foundation models, and multimodal deep learning represent important emerging directions. XAI seeks to improve transparency and clinical interpretability; federated learning may allow institutions to collaboratively train models without directly exchanging sensitive patient data; and multimodal models may integrate imaging, dosimetry, clinical, and biological information within unified analytical systems.

These technologies could potentially expand AI applications across diagnostic imaging, adaptive radiotherapy, quality management, and precision medicine. However, their future clinical value will depend on rigorous external validation, interoperability, regulatory compliance, privacy protection, and evidence demonstrating improvements in clinically meaningful outcomes. The original study similarly identifies these emerging technologies as potential drivers of future transformation in medical physics.

6 . Previous Studies and Critical Literature Review

The period between 2020 and 2025 witnessed a noticeable shift in the nature of research addressing artificial intelligence (AI) in medical physics. Earlier studies primarily focused on demonstrating the ability of machine learning and deep learning algorithms to perform individual technical tasks, whereas more recent research has increasingly emphasized their integration into clinical workflows, external validation, generalizability, reliability, and patient safety. This transition reflects the growing maturity of AI research in medical physics, where the central question is no longer simply whether an algorithm can perform a particular task, but whether its performance can be translated into safe, reproducible, and clinically meaningful outcomes.

At an early stage of this development, Cui et al. (2020) provided a foundational review of machine learning and deep learning specifically directed toward medical physicists. Their work addressed data preprocessing, model development, training, validation, and evaluation, emphasizing that high algorithmic accuracy alone does not guarantee successful clinical implementation. Dataset quality, data partitioning strategies, overfitting, and external validation were identified as major determinants of real-world performance. An important contribution of this study was therefore its shift from merely discussing algorithm capabilities toward establishing methodological conditions for developing reliable AI systems in medical physics.

Similarly, Shen et al. (2020) examined the foundations and major applications of deep learning in medical physics, highlighting its capacity to address complex problems in medical image analysis, segmentation, reconstruction, prediction, and optimization. Although the authors demonstrated the considerable potential of deep neural networks, they also emphasized challenges associated with large training-data requirements and the limited interpretability of many deep learning architectures. Their findings contributed to a more balanced understanding of AI by suggesting that predictive performance should be evaluated together with interpretability, robustness, and clinical validation rather than treated as an isolated measure of success.

Within radiation oncology, Siddique and Chow (2020) reviewed the application of AI across multiple stages of radiotherapy, including medical imaging, patient simulation, treatment planning, quality assurance, and radiation delivery. Their review suggested that AI could reduce repetitive manual tasks, improve workflow efficiency, and increase treatment consistency. Nevertheless, many of the applications discussed remained at relatively early stages of clinical translation, indicating that the strength of technical evidence was considerably greater than the evidence demonstrating sustained improvements in clinical outcomes. This distinction between technological feasibility and clinical benefit subsequently became increasingly important in the literature.

A related technological perspective was presented by Sheng (2020), who analyzed the use of AI throughout the radiotherapy workflow. The review demonstrated that AI could contribute not only to the automation of routine activities but also to advanced functions such as real-time image enhancement, adaptive radiotherapy, personalized treatment planning, and large-scale patient-data analysis. However, the study also suggested that achieving these benefits requires standardized and secure integration of clinical data across information systems. Thus, the clinical value of AI depends not simply on algorithm design but also on the digital infrastructure within which such algorithms operate.

In the area of medical imaging, Wang et al. (2021) reviewed deep-learning approaches for medical image synthesis and cross-modality image translation, including synthetic image generation and transformations between CT and MRI. Their analysis indicated that these approaches may reduce the need for additional imaging procedures and facilitate radiotherapy planning. Importantly, however, they cautioned that synthetic images should not be judged exclusively according to visual similarity. Their quantitative fidelity and impact on subsequent dosimetric calculations and clinical decisions must also be established. This consideration is particularly important in medical physics, where small image inaccuracies can potentially influence tissue characterization, dose calculation, or treatment planning.

Expanding this perspective, Barragán-Montero et al. (2021) reviewed AI and machine learning applications in medical imaging from a technical standpoint, discussing image reconstruction, processing, segmentation, and quantitative analysis. Their study demonstrated that AI was becoming increasingly integrated into medical imaging workflows. Nevertheless, the authors highlighted persistent concerns related to validation, interpretability, differences among imaging devices, institutional protocols, and patient populations. Their findings therefore challenged the assumption that good performance within a single institution automatically indicates broader clinical applicability.

The changing professional role of the medical physicist was examined by Zanca et al. (2021). Rather than focusing exclusively on algorithm performance, the authors emphasized the competencies that medical physicists would require in an AI-enabled healthcare environment. Their study argued that medical physicists increasingly need knowledge of data science, algorithms, model validation, and risk assessment in addition to their traditional expertise in measurement, calibration, dosimetry, and quality assurance. This work is

particularly important because it situates human expertise as a central determinant of successful AI implementation rather than assuming that technological availability alone will generate clinical value.

Likewise, Cusumano et al. (2021) explored AI applications in magnetic resonance-guided radiotherapy. They demonstrated how AI could support automatic segmentation, image analysis, and adaptive treatment processes based on anatomical changes identified during therapy. These applications may increase precision while reducing the time required for adaptive workflows. Nevertheless, the authors emphasized that greater automation would reshape rather than eliminate the role of the medical physicist, whose responsibilities would increasingly include algorithm verification, system supervision, risk management, and interpretation of automated outputs.

From a methodological perspective, El Naqa et al. (2021) addressed an equally important issue by proposing guidelines for publishing AI studies in medical physics. The authors emphasized transparent reporting of datasets, model architecture, training procedures, validation methods, and comparative analyses. Their contribution highlights a fundamental problem in AI research: claims of algorithmic superiority are meaningful only when the scientific evidence supporting those claims can be evaluated, reproduced, and independently validated. Accordingly, methodological transparency emerged as an essential component of trustworthy AI research.

A broader review by Fu et al. (2022) examined AI applications throughout radiation therapy, including image reconstruction, segmentation, treatment planning, quality assurance, and outcome prediction. The authors demonstrated substantial progress in deep-learning-based automation across several components of the radiotherapy workflow. However, they also observed that many models had been developed using datasets from individual institutions. Consequently, strong internal performance did not necessarily guarantee successful generalization across different scanners, treatment systems, institutional protocols, or patient groups. This distinction between algorithmic performance and clinical robustness represents one of the most important themes emerging from contemporary research.

The concept of trustworthy AI was addressed explicitly by Hasani et al. (2022) in the context of medical imaging. They argued that clinical AI should be evaluated not only according to sensitivity, specificity, or overall accuracy, but also according to transparency, robustness, fairness, interpretability, bias management, and appropriate human oversight. Their study marked an important transition from viewing AI as an isolated computational system toward understanding it as a component of a broader clinical decision-making environment in which responsibility, accountability, and patient safety remain fundamental.

A further contribution was made by Claessens et al. (2022), who examined quality assurance for AI-based systems in radiation therapy. They noted that traditional QA procedures were primarily designed for deterministic systems governed by predefined rules, whereas data-driven models may demonstrate performance variations when patient populations, input distributions, or operational environments change. Consequently, AI-based systems require additional mechanisms for preclinical validation, continuous monitoring, error detection, and post-deployment performance assessment. This represents a significant shift in the concept of quality assurance, from periodic testing of equipment toward lifecycle monitoring of intelligent systems.

In treatment planning, Nguyen et al. (2022) reviewed developments in automated radiotherapy planning using knowledge-based approaches, machine learning, and deep learning. Their findings indicated that AI-supported planning can reduce variability among planners, improve treatment-plan consistency, and shorten planning time. However, the authors also showed that treatment-plan quality cannot be reduced to the fulfillment of a limited set of dosimetric constraints. Clinical acceptability requires balancing multiple objectives and considering patient-specific disease characteristics, anatomical factors, and therapeutic priorities.

As the field matured further, Liu et al. (2023) presented a comprehensive overview of AI in medical physics and radiation oncology, covering imaging, segmentation, treatment planning, image guidance, quality assurance, and outcome prediction. They argued that AI could evolve beyond task automation toward supporting adaptive and personalized radiotherapy. However, this potential remains dependent on multi-institutional datasets, external validation, and stronger associations between algorithm performance and clinically meaningful outcomes. Their analysis therefore provides a particularly relevant foundation for understanding the broader transformation of medical physics under AI-assisted practice.

The clinical implementation of AI was explored further by Landry et al. (2023), who examined the role of AI within routine radiotherapy practice. Their review suggested that applications such as automatic segmentation and automated treatment planning have reached comparatively higher levels of technological maturity. Nevertheless, adoption remains heterogeneous because of differences in institutional infrastructure, workflow organization, local validation processes, staff expertise, and clinician confidence. Their findings demonstrate that a technically successful AI solution does not automatically become a clinically successful one; organizational context and human workflow remain essential determinants of implementation effectiveness.

The influence of AI on the professional practice of medical physicists was also examined by Fiagbedzi et al. (2023). They found that AI can support imaging, treatment planning, prediction, verification, and quality assurance, but should not be interpreted as a replacement for medical physicists. Instead, professional responsibilities are expected to evolve toward algorithm supervision, performance verification, safety assessment, and intervention in complex or atypical cases. Their study strongly supports a human–AI collaboration model, in

which AI augments rather than substitutes professional expertise.

In automatic segmentation, Isaksson et al. (2023) reviewed a substantial body of literature concerning deep-learning-based segmentation for radiotherapy. Their analysis confirmed rapid development in this field across multiple anatomical sites and algorithmic architectures. However, substantial heterogeneity was observed in datasets, evaluation methods, validation strategies, and performance metrics. This methodological variability limits direct comparison between studies. More importantly, a high Dice similarity coefficient alone does not necessarily demonstrate clinical acceptability, since geometric agreement may not fully capture clinically significant boundary errors or their subsequent dosimetric consequences.

Moving toward multi-institutional validation, Kalendralis et al. (2023) investigated AI-supported quality assurance of radiotherapy treatment plans in a multicentric context. Their approach demonstrated the potential of machine learning to identify treatment plans that may require additional review. The multicenter nature of this work represented an important advance over single-institution research. Nevertheless, the dependence of model performance on historical clinical data and institutional treatment standards still suggests that local validation remains necessary before clinical deployment in new settings.

An especially relevant perspective for lower-resource healthcare systems was provided by Manson et al. (2023), who examined Africa's readiness for AI implementation in clinical radiotherapy and emphasized the leadership role of medical physicists. Their analysis demonstrated that barriers to AI adoption extend beyond algorithm development to include digital infrastructure, data availability, professional training, governance mechanisms, and institutional resources. This finding is particularly significant because models developed in technologically advanced healthcare systems may not maintain equivalent performance when transferred directly to African or other resource-constrained clinical environments without contextual adaptation and external validation.

Research published in 2024 increasingly emphasized reliability and uncertainty. Wahid et al. (2024) systematically examined uncertainty quantification in AI applications for radiotherapy. Their work identified a fundamental limitation of many AI models: algorithms often provide predictions without adequately communicating how uncertain those predictions are. Uncertainty estimation can therefore help detect cases that fall outside the model's training distribution and identify situations requiring expert intervention. This shifts the central question from simply asking, “Is the model accurate?” toward the clinically more relevant question, “When should the model be trusted, and when should its output be questioned?”

A systematic review and meta-analysis by Wang et al. (2024) evaluated deep-learning applications for CT-based lung cancer segmentation across 37 studies. Their findings demonstrated generally promising pooled segmentation performance, with a Dice coefficient of approximately 0.79 and improvements in more recent studies. However, the authors also identified methodological and reporting concerns related to dataset characterization and potential bias. Their findings are particularly valuable because they demonstrate that improving numerical performance does not automatically eliminate problems of generalizability or methodological quality.

Similarly, Shan et al. (2024) reviewed AI applications across different stages of radiotherapy and demonstrated their potential in image processing, organ and tumor segmentation, treatment planning, dose prediction, and quality assurance. Nevertheless, they emphasized that AI-based quality assurance should function primarily as a decision-support and alerting mechanism for medical physicists rather than as an autonomous replacement for established clinical verification procedures. Their conclusions are therefore consistent with the growing emphasis on the human-in-the-loop model for safe AI implementation.

The application of AI to quality assurance was also reviewed by Ono et al. (2024), particularly in relation to machine-specific and patient-specific QA in radiation therapy. Their analysis showed that predictive models may assist in identifying abnormal equipment behavior and potentially reduce some routine measurement burdens. However, rare errors may still have substantial clinical consequences even when their overall probability is low. For this reason, AI-based prediction cannot currently eliminate the need for physics-based verification, highlighting the continued importance of balancing operational efficiency with radiation safety.

In the area of automatic contouring, Erdur et al. (2024) examined deep-learning approaches for auto segmentation in radiotherapy treatment planning. The review demonstrated that contemporary AI systems can achieve high levels of accuracy for a variety of organs at risk. However, performance varies considerably according to anatomical structure, imaging modality, dataset composition, and model architecture. These findings suggest that evaluation should not depend on a single global performance measure. Instead, clinically meaningful assessment should integrate geometric similarity, expert evaluation, dosimetry consequences, editing time, and workflow efficiency.

Research published in 2025 increasingly reflects the transition from algorithm development toward structured clinical implementation. Rusanov et al. (2025) proposed guidance for selecting and evaluating AI-based auto segmentation systems for radiotherapy, emphasizing the importance of testing performance on locally representative datasets before implementation. Similarly, Poel et al. (2025) proposed a multidimensional technical evaluation framework for auto segmentation models that integrates geometric performance, expert assessment, time efficiency, and dosimetry relevance. This approach directly addresses an important limitation of previous research that relied excessively on single geometric

metrics. In parallel, Jia et al. (2025) examined the growing use of AI within radiation oncology clinical research and highlighted the continuing need for standardized validation, reporting, quality assurance, and clinical evaluation. Collectively, these studies suggest that contemporary research is moving beyond demonstrating that AI can perform medical-physics tasks toward defining the conditions under which AI can be safely, consistently, and responsibly incorporated into clinical practice.

Critical Synthesis of Previous Studies

A comparative analysis of the literature reveals broad agreement that AI has generated meaningful technological advances in several areas of medical physics, particularly image reconstruction and enhancement, automatic segmentation, radiotherapy treatment planning, dose prediction, quality assurance, adaptive radiotherapy, and clinical outcome prediction. Nevertheless, the maturity of evidence varies substantially across applications. Automatic segmentation and image analysis possess a relatively extensive research base, whereas fully autonomous therapeutic decision-making remains considerably less established.

A chronological change in research emphasis can also be identified. Studies published during 2020–2021 largely emphasized technological capabilities and algorithmic performance (Cui et al., 2020; Sheng, 2020; Barragán-Montero et al., 2021). In contrast, studies published between 2022 and 2025 increasingly focused on trustworthiness, external validation, quality assurance, uncertainty quantification, generalizability, and clinical integration (Hasani et al., 2022; Claessens et al., 2022; Wahid et al., 2024; Rusanov et al., 2025). This progression indicates that the scientific discussion surrounding AI in medical physics is moving from technological feasibility toward clinical reliability.

Despite consistently encouraging findings, the literature also reveals a recurring methodological concern: many investigations evaluate AI primarily through technical measures such as the Dice coefficient, classification accuracy, sensitivity, specificity, or dosimetry prediction error without consistently demonstrating that improvements in these indicators produce meaningful improvements in patient safety, treatment outcomes, or clinical decision-making. Furthermore, many models are trained and evaluated retrospectively using data from single institutions. Variations in scanners, treatment machines, imaging protocols, patient populations, annotation practices, and clinical workflows may therefore reduce their generalizability.

The literature consequently reveals a significant gap between computational superiority and clinical readiness. A model may demonstrate excellent internal validation performance while experiencing degradation when implemented in another hospital, on another device, or within a population insufficiently represented in its training data. External validation, uncertainty estimation, continuous performance monitoring, and expert supervision have therefore become increasingly important themes. In this context, the medical physicist continues to play a central role in model verification, safety assessment, interpretation, and clinical governance rather than becoming redundant through automation.

7. Research Gap

Despite the rapid expansion of research on artificial intelligence in medical physics, much of the existing literature has examined individual applications or isolated stages of the clinical workflow, such as image reconstruction, automatic segmentation, treatment planning, or quality assurance. Relatively few reviews have integrated these applications within a unified analytical framework that simultaneously considers technical performance, clinical value, patient safety, generalizability, ethical and regulatory requirements, and the evolving role of the medical physicist.

A second important limitation is the dominance of algorithm-centered evaluation. Many studies emphasize predictive or geometric performance, whereas fewer provide strong evidence that improvements in algorithmic metrics translate into better clinically meaningful outcomes. External multicenter validation also remains limited for many AI models, while retrospective and single-institution studies continue to represent a considerable proportion of the evidence base.

Furthermore, existing literature remains geographically unbalanced. Most AI systems have been developed and validated within technologically advanced healthcare environments, while evidence from low- and middle-resource settings, particularly African healthcare systems, remains comparatively limited. Differences in equipment, data quality, digital infrastructure, professional competencies, and regulatory environments may influence AI performance and restrict direct transferability.

Another emerging gap concerns rapidly developing areas such as explainable AI, uncertainty quantification, federated learning, generative AI, foundation models, and multimodal learning. Although these technologies have considerable potential to reshape medical physics, they have not yet been sufficiently integrated into a comprehensive critical framework linking technological innovation with clinical safety, professional accountability, and implementation readiness.

Accordingly, the principal research gap lies in the need for an integrative critical review that moves beyond asking how accurately AI performs toward examining when, where, and under what conditions AI can be safely trusted and clinically implemented in medical physics.

8 . Scientific Contribution of the Present Study

The present study addresses this gap by providing an integrated descriptive, comparative, analytical, and critical framework for evaluating modern applications of artificial intelligence in medical physics. Rather than simply summarizing previously reported applications, the study compares the existing evidence according to technological maturity, methodological strength, clinical applicability, limitations, generalizability, validation requirements, and patient-safety implications.

A particular contribution of the study is its integration of medical imaging, radiation therapy and treatment planning, quality assurance, precision medicine, and emerging AI technologies within a unified conceptual perspective. This approach places patient safety and human–AI collaboration at the center of AI evaluation and recognizes the medical physicist as a critical professional responsible for validation, interpretation, governance, and safe clinical implementation.

The study further proposes a conceptual transition from assessing AI primarily in terms of AI accuracy toward evaluating clinically trustworthy AI. Within this perspective, clinical readiness should be viewed as the combined outcome of algorithmic performance, representative data quality, external validation, interpretability, uncertainty quantification, professional oversight, regulatory compliance, workflow integration, and demonstrated clinical value.

Accordingly, the scientific contribution of the study lies in reframing the central question in AI-based medical physics. Rather than asking only, "Can artificial intelligence perform this medical-physics task?", the study emphasizes the more clinically significant question: "Can artificial intelligence perform the task reliably, generalizable, transparently, and safely while preserving professional oversight and improving clinically meaningful outcomes?"

9 . Methodology

This study adopted a descriptive, comparative, analytical, and critical review approach**,** which is appropriate for the theoretical nature of the research and its aim of reviewing and evaluating the contemporary scientific literature on modern applications of artificial intelligence (AI) in medical physics. Relevant studies were collected, organized, and classified according to the major domains of AI application, particularly medical imaging, radiation oncology and treatment planning, quality assurance and patient safety, precision medicine, emerging AI technologies, and challenges associated with clinical implementation. Rather than merely providing a descriptive or narrative summary of previous studies, the review employed a comparative and critical analytical perspective to examine their methodologies, findings, and conclusions, identify areas of convergence and divergence, and interpret variations in reported outcomes in relation to differences in AI techniques, algorithms, datasets, clinical environments, and levels of validation. The available evidence was also critically evaluated in terms of methodological strengths and limitations, generalizability, data quality and representativeness, external validation, model interpretability, and ethical, regulatory, and clinical safety considerations. A critical narrative synthesis was subsequently employed to integrate heterogeneous findings and develop a coherent interpretation of the actual contribution of AI to medical physics, while avoiding the assumption that superior algorithmic performance or technical accuracy necessarily translates into improved clinical outcomes. Through this approach, the study sought to identify common trends, inconsistencies, methodological and knowledge gaps, and areas requiring further external validation and clinical investigation, ultimately providing future research directions and practical recommendations for the safer, more reliable, and effective integration of AI into medical physics.

10 Results and Discussion

The critical synthesis of the reviewed literature indicates that artificial intelligence has evolved from an experimental computational tool into an increasingly influential component of contemporary medical physics. Across the studies examined, the strongest and most consistent evidence concerns medical imaging, automated segmentation, radiotherapy treatment planning, dose prediction, and quality assurance. However, the present review also demonstrates that technological maturity is uneven across these applications and that high computational performance should not automatically be interpreted as evidence of clinical readiness. This finding is consistent with Cui et al. (2020), who emphasized that the effectiveness of machine- and deep-learning models depends not only on predictive accuracy but also on data quality, model validation, and control of overfitting. Similarly, Shen et al. (2020) showed that deep learning offers substantial advantages for segmentation, reconstruction, and prediction, while simultaneously raising concerns regarding interpretability and dependence on large, representative datasets. Taken together, these findings suggest that AI performance in medical physics should be assessed as a multidimensional construct rather than through isolated accuracy measures.

AI in Medical Imaging: From Technical Performance to Clinical Utility

One of the clearest findings of the present review is that medical imaging represents one of the most mature fields of AI application in medical physics. Deep learning has demonstrated substantial capabilities in image reconstruction, noise reduction, lesion identification, automated segmentation, and cross-modality image synthesis. This result agrees with Wang et al. (2021), who found that deep-learning-based image synthesis can support CT–MRI translation and potentially reduce the need for additional imaging procedures. It also corresponds with Barragán-Montero et al. (2021), who identified image reconstruction, segmentation, processing, and quantitative image analysis as major areas in which AI has produced measurable technological advances.

Nevertheless, the present analysis indicates that the clinical interpretation of these achievements requires caution. A visually convincing synthetic image, for example, does not necessarily preserve all quantitative information required for dosimetry or treatment planning. This observation is particularly important because medical physics differs from purely diagnostic image interpretation: relatively small alterations in pixel intensity or anatomical boundaries may propagate into dose calculations or target delineation. The findings of Wang et al. (2021) support this interpretation by.

emphasizing the need to evaluate synthetic images in relation to their downstream clinical and quantitative consequences rather than according to image similarity alone.

This critical interpretation is further strengthened by Wang et al. (2024), whose systematic review and meta-analysis of CT-based lung cancer segmentation reported promising pooled performance, with an approximate Dice coefficient of 0.79, while simultaneously identifying methodological limitations and potential sources of bias. The apparent contradiction between good average segmentation performance and continuing methodological concerns is highly informative. It indicates that increasing numerical accuracy does not necessarily eliminate problems of generalization, dataset heterogeneity, or clinical reliability. Thus, the present study argues that geometric performance metrics should be treated as necessary but insufficient indicators of successful AI implementation

AI in Radiotherapy and Treatment Planning

The reviewed evidence also demonstrates strong agreement concerning the potential of AI to transform radiotherapy. Applications include target and organ-at-risk delineation, dose prediction, treatment-plan optimization, adaptive radiotherapy, and automated treatment planning. This result is consistent with Siddique and Chow (2020), who concluded that AI could improve efficiency across multiple stages of the radiotherapy workflow, and with Sheng (2020), who highlighted its capacity to support image processing, adaptive treatment, personalized planning, and large-scale clinical-data analysis.

Similarly, Fu et al. (2022) documented substantial progress in AI-supported image reconstruction, segmentation, treatment planning, quality assurance, and clinical outcome prediction. Their results reinforce the present review's conclusion that radiotherapy represents one of the areas where AI may produce the greatest efficiency gains. However, Fu et al. also observed that many algorithms had been developed using single-institution datasets, thereby limiting confidence in their performance across different scanners, treatment systems, protocols, and populations. This finding provides an important explanation for why impressive research results have not always translated into equally rapid clinical adoption.

The present analysis therefore distinguishes between workflow automation and clinical intelligence. Automated planning may shorten treatment-planning time and reduce inter-planner variability, but these benefits do not necessarily imply that the system independently understands the clinical priorities underlying treatment decisions. This interpretation is supported by Nguyen et al. (2022), who reported that automated planning can improve consistency and efficiency but also stressed that plan quality cannot be reduced to a limited number of dosimetry objectives. Patient anatomy, disease characteristics, organ protection, and therapeutic priorities remain multidimensional considerations requiring professional clinical judgment.

The findings are also compatible with Cusumano et al. (2021), who demonstrated the potential of AI within MR-guided and adaptive radiotherapy. Their results suggest that AI can accelerate segmentation and facilitate treatment adaptation in response to anatomical changes. Nevertheless, the present study interprets this development not as the disappearance of medical-physics expertise but as a redistribution of professional responsibilities. As automation increases, verification, algorithm supervision, exception management, and risk assessment become more important rather than less important.

Automatic Segmentation: Strong Evidence but Incomplete Clinical Validation

Automatic segmentation emerged from the reviewed literature as one of the most extensively investigated AI applications. Studies generally report considerable improvements in segmentation speed and increasingly high geometric agreement with expert-defined contours. Isaksson et al. (2023) confirmed the rapid expansion of deep-learning segmentation across anatomical sites, while Erdur et al. (2024) reported high levels of performance for several organs at risk.

However, the present analysis reveals an important limitation in how segmentation success has often been defined. Much of the literature relies heavily on geometric measures, particularly the Dice similarity coefficient. Although these indicators provide useful information about spatial agreement, they do not necessarily indicate whether an error occurs in a clinically important region or whether it alters the final dose distribution. This criticism is consistent with Isaksson et al. (2023), who identified substantial heterogeneity in segmentation datasets, validation strategies, and evaluation metrics.

The evolution of the literature toward more comprehensive assessment is therefore an important positive development. Poel et al. (2025) proposed a multifaceted framework combining geometric measures with expert assessment, editing time, and dosimetry consequences, while Rusanov et al. (2025) emphasized the necessity of evaluating auto segmentation systems using locally representative clinical data before implementation. These recent contributions

strongly support the present study's conclusion that AI evaluation is moving from isolated computational metrics toward multidimensional measures of clinical usefulness

Quality Assurance and Patient Safety

Another major finding is that AI has the potential to shift quality assurance from predominantly reactive procedures toward predictive and risk-based quality management. Machine-learning algorithms can analyze historical equipment and treatment data, identify deviations, predict failures, and prioritize cases requiring human inspection. This conclusion is consistent with Claessens et al. (2022), who argued that AI introduces a new quality-assurance paradigm because data-driven systems differ fundamentally from conventional deterministic software. The multicenter findings reported by Kalendralis et al. (2023) provide additional support for AI-assisted radiotherapy plan QA, demonstrating that machine-learning systems can help identify treatment plans requiring further evaluation. Compared with single-center studies, this multicentric approach improves the strength of the evidence because it exposes models to greater institutional variability. Nevertheless, even multicenter validation does not completely solve the transferability problem, as differences in treatment standards, equipment, and clinical protocols can still affect performance.

This interpretation agrees with Ono et al. (2024), who found that AI can assist both machine-specific and patient-specific QA but cannot currently replace physics-based verification. This limitation deserves particular emphasis. In safety-critical fields such as radiation therapy, very rare errors may have disproportionately serious consequences. Consequently, optimizing average predictive accuracy is insufficient if the model remains vulnerable to uncommon but clinically dangerous cases. The present review therefore interprets AI-based QA most appropriately as an additional decision-support and risk-detection layer, rather than an autonomous substitute for established quality-assurance procedures.

The same position is supported by Shan et al. (2024), who concluded that AI-based QA should primarily assist medical physicists by generating warnings and prioritizing potentially problematic cases. Agreement across these studies provides strong evidence in favor of a human-in-the-loop model for safety-critical applications.

The Difference Between Algorithmic Accuracy and Clinical Trustworthiness

Perhaps the most important cross-cutting result of the present study is the persistent gap between algorithmic accuracy and clinical trustworthiness. Earlier studies tended to emphasize improvements in predictive accuracy and automation, whereas later studies increasingly questioned whether high-performance algorithms remain reliable when exposed to different clinical populations and operating conditions. The progression from Cui et al. (2020) and Sheng (2020) toward Hasani et al. (2022), Wahid et al. (2024), and Rusanov et al. (2025) illustrates this conceptual evolution clearly.

Hasani et al. (2022) argued that trustworthy medical AI should incorporate robustness, transparency, fairness, interpretability, and human oversight in addition to predictive accuracy. The present review strongly supports this broader definition. An algorithm that produces highly accurate predictions but cannot reveal uncertainty, performs inconsistently across populations, or cannot be independently validated should not be considered clinically trustworthy merely because its average performance is high.

The systematic review of uncertainty quantification by Wahid et al. (2024) provides particularly important support for this interpretation. Their findings demonstrate that AI systems frequently communicate outputs without sufficiently communicating the uncertainty associated with those outputs. In clinical medical physics, this represents a significant limitation because professionals need to distinguish routine cases for which automated predictions are reliable from unusual cases requiring expert intervention. Thus, uncertainty quantification should not be considered an optional mathematical enhancement; it represents an important component of patient-safety architecture.

External Validation, Generalizability, and Dataset Bias

The present review further identifies insufficient external validation as one of the most persistent weaknesses across the AI literature. Many studies use retrospective datasets from individual institutions, and model development often occurs under controlled conditions that differ substantially from real-world clinical environments. The concern raised by Fu et al. (2022) regarding single-institution training is consistent with the findings of Barragán-Montero et al. (2021) concerning variations in scanners, imaging protocols, and populations.

This problem can be interpreted as a form of dataset-context dependency. AI systems do not learn universal clinical laws independently of their training data; rather, they learn patterns embedded within particular datasets. Consequently, a model may unintentionally learn institution-specific imaging characteristics, annotation practices, demographic patterns, or equipment-dependent features. When deployed elsewhere, these relationships may no longer hold.

The present study therefore supports the increasing emphasis on local and external validation. Rusanov et al. (2025) explicitly recommended testing AI auto

segmentation systems on locally representative data before clinical implementation. This recommendation is particularly important because external validation should not be regarded as a final procedural step after model development, but as a fundamental requirement for establishing clinical transportability.

Resource-Limited Environments and the African Context

The geographical distribution of the available evidence reveals another important weakness. Most advanced AI models have been developed and evaluated in technologically well-resourced healthcare environments. The present review therefore finds that conclusions about the universal applicability of AI should be interpreted carefully, especially in low- and middle-resource healthcare systems.

This conclusion is strongly supported by Manson et al. (2023), who examined Africa's readiness for AI-assisted clinical radiotherapy. Their findings indicate that AI adoption depends on more than access to software or algorithms. Digital infrastructure, standardized datasets, equipment availability, professional training, institutional governance, and regulatory capacity all influence implementation.

This result challenges a technology-centered assumption that importing a successful AI system will automatically reproduce the outcomes achieved in its development environment. In African contexts, equipment heterogeneity, limited digitization, smaller datasets, and constrained technical resources may influence both algorithm performance and implementation sustainability. Therefore, the present study argues that contextual validation should complement technical validation, especially when AI systems are transferred across substantially different healthcare environments.

Human–AI Collaboration and the Changing Role of Medical Physicists

A highly consistent finding across the literature is that AI is more likely to transform than eliminate the role of medical physicists. The present review therefore rejects replacement-based interpretations of AI adoption. Instead, it supports an augmentation model in which automated systems perform repetitive computational tasks while medical physicists increasingly supervise algorithms, validate outputs, manage exceptions, assess safety, and maintain clinical accountability.

This conclusion is consistent with Zanca et al. (2021), who argued that future medical physicists will require stronger competencies in data science, machine learning, and algorithm validation. It also agrees with Fiagbedzi et al. (2023), who found that AI is likely to reshape professional activities toward supervision and performance verification rather than eliminate the profession.

The agreement between these studies and the present review has important implications for professional education. If AI implementation changes the nature of medical physics work, training programs should evolve accordingly. Competence in dosimetry, radiation safety, imaging physics, and quality assurance will remain essential, but these traditional skills increasingly need to be complemented by knowledge of data governance, algorithmic bias, model validation, uncertainty, and AI risk management.

Precision Medicine and Personalized Radiotherapy

The literature further indicates that AI could expand medical physics beyond optimization of physical dose delivery toward more individualized treatment strategies. By integrating imaging information, radiomics, dosimetry, clinical variables, and potentially genomic information, AI may contribute to treatment-response prediction, toxicity estimation, and individualized risk assessment.

This finding is consistent with the broader precision-medicine perspective reflected in Liu et al. (2023), who described the potential evolution of AI from workflow automation toward adaptive and personalized radiation oncology. However, the present study interprets the evidence in this area as promising but less mature than the evidence supporting imaging and segmentation applications. Personalized predictive models require heterogeneous multimodal datasets and stronger prospective validation because the risk of confounding and population-specific bias increases as the complexity of the input information expands.

Therefore, while precision medicine represents one of the most important long-term directions for AI-assisted medical physics, claims concerning personalized outcome prediction should be made more cautiously than claims concerning relatively bounded technical tasks such as segmentation.

Methodological Criticism of the Existing Evidence

A critical comparison of the reviewed studies reveals several recurrent methodological limitations. First, retrospective research remains dominant. Such datasets are useful for algorithm development but may not reproduce the complexity, uncertainty, missing data, and workflow pressures encountered prospectively in clinical practice. Second, sample composition and patient demographics are not always sufficiently diverse, raising concerns about algorithmic bias and population transferability. Third, studies frequently report different outcome measures, making quantitative comparison difficult.

Fourth, many investigations focus on whether an algorithm can outperform or approximate an expert on an individual task without evaluating the effect of human–AI

interaction on the complete clinical workflow. This is a significant

limitation because an algorithm may perform well independently but still introduce new workflow errors, automation bias, unnecessary verification burden, or inappropriate user confidence.

Fifth, methodological transparency remains inconsistent. This issue reinforces the recommendations of El Naqa et al. (2021) concerning detailed reporting of datasets, model architecture, validation procedures, and comparative evaluation. Reproducibility should therefore be regarded as an essential characteristic of high-quality AI research rather than merely an editorial requirement.

Overall Interpretation of the Findings

When the reviewed evidence is considered collectively, three broad stages in the development of AI research in medical physics can be identified. The first stage emphasized technical feasibility, demonstrating that machine learning and deep learning could successfully perform imaging, segmentation, planning, and prediction tasks (Cui et al., 2020; Sheng, 2020). The second stage moved toward clinical integration, examining the use of AI throughout radiotherapy workflows, automated planning, adaptive treatment, and quality assurance (Fu et al., 2022; Nguyen et al., 2022; Liu et al., 2023). The emerging third stage emphasizes clinical trustworthiness, characterized by external validation, uncertainty quantification, comprehensive evaluation, human oversight, and local implementation testing (Hasani et al., 2022; Wahid et al., 2024; Poel et al., 2025; Rusanov et al., 2025).

This progression represents one of the principal findings of the present review. It suggests that the scientific maturity of AI in medical physics should no longer be assessed primarily according to whether increasingly sophisticated algorithms can be developed. The more significant challenge now concerns demonstrating that these systems remain reliable when transferred from research datasets into heterogeneous clinical environments.

Accordingly, the present study concludes that the most appropriate conceptual model for contemporary AI in medical physics is not AI replacing the medical physicist, but rather AI augmenting medical-physics expertise under structured professional oversight. This interpretation is consistent with Fiagbedzi et al. (2023) and Manson et al. (2023) and is further supported by evidence emphasizing uncertainty estimation, quality assurance, and contextual validation. The clinical value of AI therefore emerges from the interaction of algorithm performance, representative data, external validation, interpretability, workflow compatibility, uncertainty management, regulatory governance, and human expertise.

Ultimately, the reviewed evidence supports a transition from an accuracy-centered paradigm toward a clinically trustworthy AI paradigm. Under this perspective, an AI system should not be considered clinically successful merely because it achieves superior computational performance. Its true value should be judged according to whether it produces reproducible improvements in efficiency, safety, decision quality, treatment consistency, and clinically meaningful patient outcomes while remaining interpretable, auditable, and subject to professional oversight. This interpretation provides a more realistic and clinically responsible basis for the future integration of artificial intelligence into medical physics

11 .| Conclusion

This study critically reviewed the modern applications of artificial intelligence in medical physics and demonstrated that the field has reached a stage at which the central scientific concern is no longer limited to whether AI can achieve high levels of computational accuracy, but rather whether such accuracy can be translated into reliable, reproducible, safe, and clinically meaningful performance. The reviewed evidence indicates that AI has already generated substantial advances in medical imaging, automatic segmentation, treatment planning, dose prediction, quality assurance, adaptive radiotherapy, and precision medicine. Nevertheless, the degree of maturity differs considerably across these applications. Image analysis and automatic segmentation currently demonstrate stronger and more consistent evidence, whereas fully autonomous therapeutic decision-making, individualized outcome prediction, and some emerging AI applications remain less clinically established.

A major conclusion of the study is that algorithmic superiority should not be equated with clinical readiness**.** High values of accuracy, sensitivity, Dice similarity, or prediction performance remain important, but they provide only a partial representation of the clinical value of an AI system. The evidence reviewed in this study shows that models may achieve excellent internal performance while exhibiting reduced reliability when applied to different institutions, scanners, patient populations, imaging protocols, or treatment systems. This limitation is particularly important in medical physics because even small errors in segmentation, dose estimation, image reconstruction, or equipment prediction may have consequences that extend directly to patient safety.

The study further concludes that the most important conceptual transition currently occurring in the field is the movement from an accuracy-centered AI paradigm toward a clinically trustworthy AI paradigm**.** Under this broader perspective, AI should be evaluated according to the interaction of multiple dimensions, including algorithmic performance, data quality and representativeness, external validation, interpretability, uncertainty estimation,

workflow compatibility, regulatory compliance, cybersecurity, and professional oversight. Therefore, the future of AI in medical physics should not be determined merely by the development of increasingly complex algorithms, but by the development of systems capable of demonstrating stable and accountable performance in heterogeneous clinical environments.

Another important conclusion concerns the role of medical physicists. The findings strongly reject the assumption that AI will simply replace professional expertise. Instead, the evidence suggests that AI is transforming the nature of medical-physics practice. As repetitive computational tasks become increasingly automated, professional responsibilities are expected to shift toward algorithm verification, validation, quality assurance, risk management, interpretation of uncertain outputs, and clinical governance. Accordingly, the relationship between AI and medical physicists should be conceptualized as one of augmentation rather than substitution**.** The safest and most realistic implementation model remains a human-in-the-loop approach in which AI increases efficiency while qualified professionals retain responsibility for final verification and clinical accountability.

The analysis also demonstrates that quality assurance itself must evolve. Traditional QA approaches were developed primarily for deterministic equipment and software, whereas AI systems are data-dependent and may change in performance when exposed to new populations or operational environments. For this reason, AI quality assurance should be regarded as a continuous lifecycle process that includes pre-implementation validation, local testing, post-deployment monitoring, uncertainty assessment, performance drift detection, and periodic reassessment. This represents a fundamental change from checking whether a system operates correctly at one point in time toward continuously determining whether it remains clinically reliable.

Furthermore, the study identifies geographical and institutional inequalities as a major challenge to the future diffusion of AI. Most advanced AI systems have been developed and evaluated in relatively well-resourced healthcare settings, while evidence from African and other low- and middle-resource environments remains comparatively limited. This creates a significant risk of inappropriate technological transfer. An AI model trained on one healthcare system cannot automatically be assumed to perform equally well in another setting characterized by different equipment, data structures, patient demographics, digital infrastructure, and professional capacities. Thus, contextual and local validation should be treated as essential requirements rather than optional refinements.

The reviewed evidence also indicates that precision medicine represents an important future direction, particularly through the integration of imaging, dosimetry, radiomics, clinical data, and potentially genomic information. However, this area should be approached cautiously. The increasing complexity of multimodal predictive models may increase their potential clinical value while simultaneously increasing vulnerability to bias, confounding, data heterogeneity, and limited interpretability. Therefore, personalized AI-driven recommendations should require a higher level of prospective and multicenter validation than relatively bounded technical applications such as automatic segmentation.

The emergence of explainable AI, uncertainty quantification, federated learning, generative AI, foundation models, and multimodal systems also creates substantial opportunities for medical physics. These technologies may improve interpretability, facilitate collaborative learning while protecting patient privacy, and support more integrated clinical decision-making. Nevertheless, their rapid technological evolution should not lead to premature clinical adoption. Their value should ultimately be judged according to whether they improve clinically meaningful outcomes without compromising transparency, privacy, fairness, security, or professional accountability.

Overall, the study concludes that the future contribution of artificial intelligence to medical physics will depend less on achieving marginal improvements in benchmark accuracy and more on building trustworthy, explainable, externally validated, context-sensitive, and professionally supervised AI systems**.** The defining challenge for the coming stage is therefore not simply technological innovation, but the responsible translation of innovation into clinical practice. Artificial intelligence should be regarded as a powerful scientific and clinical instrument whose value is maximized when computational capability is combined with medical-physics expertise, rigorous quality assurance, ethical governance, and continuous attention to patient safety

12 . Recommendations

Based on the critical synthesis of the reviewed literature and the identified gap between algorithmic performance and clinical readiness, the study proposes the following recommendations:

1. **Establish clinically trustworthy AI as the primary framework for implementation in medical physics.** AI systems should be evaluated through an integrated framework combining algorithmic performance, robustness, interpretability, uncertainty quantification, external and local validation, patient safety, and clinical relevance rather than relying primarily on accuracy-based metrics. Before clinical deployment, particularly in high-risk applications such as radiotherapy planning, dose prediction, automatic segmentation, and quality assurance, models should undergo multicenter and locally representative validation. Medical-physics departments should also establish AI-specific quality-assurance procedures covering initial validation, data quality, performance drift, software updates, cybersecurity, and periodic

reassessment. Within this framework, qualified medical physicists should retain responsibility for verification, clinical interpretation, approval, and intervention in uncertain or atypical cases, thereby maintaining an effective human-in-the-loop model.

2. Expand prospective and real-world clinical validation. Future research should move beyond the predominance of retrospective and single-institution studies toward prospective, multicenter, and real-world investigations capable of determining whether AI produces sustainable improvements in clinical practice.
3. Standardize AI research reporting and performance evaluation. Researchers and journals should promote consistent reporting of dataset characteristics, patient populations, model architecture, training procedures, external validation, comparative methods, and clinically meaningful performance indicators to enhance transparency, reproducibility, and comparability.
4. Adopt multidimensional measures of clinical performance. Evaluation of automatic segmentation and related applications should combine geometric accuracy with dosimetry consequences, expert assessment, editing time, workflow efficiency, robustness, and clinical acceptability rather than relying exclusively on Dice coefficients or other isolated statistical metrics.
5. Strengthen AI competencies in medical-physics education and professional development. Training programs should integrate machine learning, deep learning, data science, model validation, algorithmic bias, uncertainty quantification, cybersecurity, data governance, and AI ethics while preserving essential competencies in dosimetry, imaging physics, radiation protection, and quality assurance.
6. Develop multidisciplinary governance mechanisms for clinical AI. AI implementation should involve medical physicists, clinicians, radiologists, radiation oncologists, engineers, data scientists, information-security specialists, and regulatory experts to ensure that technological performance is accompanied by clear clinical responsibility and accountability.
7. Prioritize patient safety when selecting and implementing AI systems. Healthcare institutions should assess AI technologies not only according to vendor-reported accuracy and efficiency but also according to transparency, independent validation, local compatibility, cybersecurity, traceability, maintenance requirements, and mechanisms for detecting and managing errors.
8. Develop context-sensitive AI strategies for resource-constrained healthcare systems. AI models developed in technologically advanced environments should not be transferred directly to African and other low- and middle-resource settings without local assessment of data quality, equipment compatibility, infrastructure readiness, workforce capacity, affordability, and regulatory conditions.
9. Expand African and multicounty medical datasets. Collaboration among hospitals, universities, research institutions, and professional organizations should be strengthened to establish representative datasets reflecting regional patient populations, disease patterns, imaging systems, radiotherapy equipment, and clinical practices.
10. Explore federated learning as a privacy-preserving approach to multicenter AI development. Federated approaches should be investigated where centralized sharing of patient data is difficult, while carefully evaluating interoperability, cybersecurity, data heterogeneity, privacy, and algorithmic fairness.
11. Direct emerging AI research toward clinically meaningful, explainable, and responsibly governed applications. Future research on explainable AI, generative AI, foundation models, and multimodal systems should prioritize rigorous medical-physics-specific validation, understandable model outputs, uncertainty estimation, factual reliability, privacy, cybersecurity, and protection against clinically plausible but incorrect outputs. Their effectiveness should ultimately be evaluated according to measurable clinical outcomes, including reductions in treatment-planning time and error rates, improved dose optimization and patient safety, reduced unnecessary radiation exposure, and better use of healthcare resources. Regulatory and ethical frameworks should simultaneously be developed to address continuously evolving AI systems, including model updates, performance monitoring, transparency, responsibility for errors, privacy protection, and professional accountability.
12. Preserve human–AI collaboration as the foundation of future medical-physics practice. The objective of AI integration should not be maximum automation or replacement of professional expertise, but the development of systems that augment the capabilities of medical physicists while remaining verifiable, auditable, interpretable, contextually validated, and subordinate to patient safety.

13. References

Barragán-Montero, A.M., Javaid, U., Valdes, G., Nguyen, D., Desbordes, P., Macq, B., Willems, S., Vandewinckele, L., Holmström, M., Löfman, F., Michiels, S., Souris, K., Sterpin, E., & Lee, J.A. (2021). Artificial intelligence and machine learning for medical imaging: A technology review. Physica medica : PM : an international journal devoted to the applications of physics to medicine and

biology : official journal of the *Italian Association of Biomedical Physics, 83, 242-256* .

https://doi.org/10.1016/j.ejmp.2021.04.016

Boldrini, L., Bibault, J. E., Masciocchi, C., Shen, Y., & Bittner, M. I. (2020). Artificial intelligence in radiation oncology: State of the art and future directions. The British Journal of Radiology, 93*(1108), 20190801. https://doi.org/10.1259/bjr.20190801*

Claessens, M., et al. (2022). Quality assurance for AI-based applications in radiation therapy. Seminars in Radiation Oncology.

Cui, S., Tseng, H. H., Pakela, J., Ten Haken, R. K., & El Naqa, I. (2020). Introduction to machine and deep learning for medical physicists. Medical Physics, 47*(5), e127–e147. https://doi.org/10.1002/mp.14140*

Cusumano, D., et al. (2021). Artificial intelligence in magnetic resonance guided radiotherapy: Medical and physical considerations on state of art and future perspectives. Physica Medica.

El Naqa, I., et al. (2021). AI in medical physics: Guidelines for publication. Medical Physics, 48*(9), 4711–4714. https://doi.org/10.1002/mp.15170*

Erdur, A. C., et al. (2024). Deep learning for auto segmentation for radiotherapy treatment planning: State-of-the-art and novel perspectives.

Fiagbedzi, E., et al. (2023). The influence of artificial intelligence on the work of the medical physicist in radiotherapy practice: A short review. British Journal of Radiology Open, 5*, 20230003.*

Fu, Y., Zhang, H., Morris, E. D., Glide-Hurst, C. K., Pai, S., Traverso, A., Wee, L., Hadzic, I., Lonne, P. I., Shen, C., Liu, T., & Yang, X. (2022). Artificial intelligence in radiation therapy. IEEE Transactions on Radiation and Plasma Medical Sciences, 6*(2), 158–181. https://doi.org/10.1109/TRPMS.2021.3107454*

Hasani, N., Morris, M. A., Rhamim, A., Summers, R. M., Jones, E., Siegel, E., & Saboury, B. (2022). Trustworthy artificial intelligence in medical imaging. PET Clinics, 17*(1), 1–12. https://doi.org/10.1016/j.cpet.2021.09.007*

Hosny, A., Parmar, C., Quackenbush, J., Schwartz, L. H., & Aerts, H. J. W. L. (2018). Artificial intelligence in radiology. Nature Reviews Cancer, 18*(8), 500–510. https://doi.org/10.1038/s41568-018-0016-5*

Isaksson, L. J., et al. (2023). Automatic segmentation with deep learning in radiotherapy.

Jia, X., Rong, Y., Wu, Q., Cardenas, C. E., Court, L. E., Hrinivich, W. T., Kang, H., Kovalchuk, N., Whitaker, T. J., Xiao, Y., Zhang, P., & Chen, Q. (2025). NRG Oncology assessment of artificial intelligence for automatic treatment planning in radiation therapy clinical trials: Present and future. International Journal of Radiation *Oncology, Biology, Physics, 123*(1), 282–295. https://doi.org/10.1016/j.ijrobp.2025.03.045

Kalendralis, P., et al. (2023). Automatic quality assurance of radiotherapy treatment plans using artificial intelligence: A multicentric study.

Lambin, P., Leijenaar, R. T. H., Deist, T. M., Peerlings, J., de Jong, E. E. C., van Timmeren, J., Sanduleanu, S., Larue, R. T. H. M., Even, A. J. G., Jochems, A., & Walsh, S. (2021). Radiomics and artificial intelligence in radiation oncology: Ready for clinical implementation? *Nature Reviews Clinical Oncology, 18*(9), 585–604. https://doi.org/10.1038/s41571-021-00520-0

Landry, G., et al. (2023). The role of artificial intelligence in radiotherapy clinical practice.

Liu, J., Xiao, H., Fan, J., Hu, W., Yang, Y., Dong, P., Xing, L., & Cai, J. (2023). An overview of artificial intelligence in medical physics and radiation oncology. *Journal of the National Cancer Center, 3*(3), 211–221.

Manson, E. N., et al. (2023). Africa's readiness for artificial intelligence in clinical radiotherapy delivery: Medical physicists to lead the way. *Physica Medica, 113*.

Nguyen, D., et al. (2022). Advances in automated treatment planning. *Seminars in Radiation Oncology*.

Ono, T., et al. (2024). Artificial intelligence for machine- and patient-specific quality assurance in radiation therapy.

Pesapane, F., Codari, M., & Sardanelli, F. (2020). Artificial intelligence in medical imaging: Threat or opportunity? Radiologists again at the forefront of innovation in medicine. *European Radiology Experimental, 4*(1), 35. https://doi.org/10.1186/s41747-020-00173-w

Poel, R., Rüfenacht, E., et al. (2025). A comprehensive multifaceted technical evaluation framework for implementation of auto-segmentation models in radiotherapy.

Rusanov, B., et al. (2025). Guidance on selecting and evaluating AI auto-segmentation solutions in radiotherapy.

Shan, G., et al. (2024). A review of artificial intelligence application for radiotherapy.

Shen, C., et al. (2020). An introduction to deep learning in medical physics. *Medical Physics*.

Sheng, K. (2020). Artificial intelligence in radiotherapy: A technological review. *Frontiers of Medicine, 14*(4), 431–449. https://doi.org/10.1007/s11684-020-0761-1

Siddique, S., & Chow, J. C. L. (2020). Artificial intelligence in radiotherapy. *Reports of Practical Oncology and Radiotherapy*.

Thompson, R. F., Valdes, G., Fuller, C. D., Carpenter, C. M., Morin, O., Aneja, S., Lindsay, W. D., Aerts, H. J. W. L., Agrimson, B., Beaulieu, C. F., et al. (2020). Artificial intelligence in radiation oncology: A specialty-wide disruptive transformation? *Radiotherapy* and Oncology, 151, 1–7. https://doi.org/10.1016/j.radonc.2020.07.030

Topol, E. (2019). High-performance medicine: The convergence of human and artificial intelligence. Nature Medicine, 25(1), 44–56. https://doi.org/10.1038/s41591-018-0300-7

Wahid, K. A., et al. (2024). Artificial intelligence uncertainty quantification in radiotherapy applications: A systematic review.

Wang, T., Lei, Y., Fu, Y., Wynne, J. F., Curran, W. J., Liu, T., & Yang, X. (2021). A review on medical imaging synthesis using deep learning and its clinical applications. Journal of Applied Clinical Medical Physics, 22(1), 11–36. https://doi.org/10.1002/acm2.13121

Wang, T. W., Hong, J. S., Huang, J. W., Liao, C. Y., Lu, C. F., & Wu, Y. T. (2024). Systematic review and meta-analysis of deep learning applications in computed tomography lung cancer segmentation. Radiotherapy and Oncology, 197, 110344. https://doi.org/10.1016/j.radonc.2024.110344

Zanca, F., Hernandez-Giron, I., Avanzo, M., Guidi, G., Crijns, W., Diaz, O., Kagadis, G. C., Rampado, O., Lønne, P. I., Ken, S., Colgan, N., Zaidi, H., Zakaria, G. A., & Kortesniemi, M. (2021). Expanding the medical physicist curricular and professional programmer to include artificial intelligence. Physica Medica, 83, 174–183. https://doi.org/10.1016/j.ejmp.2021.01.069