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Africa's readiness for artificial intelligence in clinical radiotherapy delivery: Medical physicists to lead the way

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ABSTRACT

Background: There have been several proposals by researchers for the introduction of Artificial Intelligence (AI) technology due to its promising role in radiotherapy practice. However, prior to the introduction of the technology, there are certain general recommendations that must be achieved. Also, the current challenges of AI must be addressed. In this review, we assess how Africa is prepared for the integration of AI technology into radiotherapy service delivery.
Methods: To assess the readiness of Africa for integration of AI in radiotherapy services delivery, a narrative review of the available literature from PubMed, Science Direct, Google Scholar, and Scopus was conducted in the English language using search terms such as Artificial Intelligence, Radiotherapy in Africa, Machine Learning, Deep Learning, and Quality Assurance.
Results: We identified a number of issues that could limit the successful integration of AI technology into radiotherapy practice. The major issues include insufficient data for training and validation of AI models, lack of educational curriculum for AI radiotherapy-related courses, no/limited AI teaching professionals, funding, and lack of AI technology and resources. Solutions identified to facilitate smooth implementation of the technology into radiotherapy practices within the region include: creating an accessible national data bank, integrating AI radiotherapy training programs into Africa's educational curriculum, investing in AI technology and resources such as electronic health records and cloud storage, and creation of legal laws and policies to support the use of the technology. These identified solutions need to be implemented on the background of creating awareness among health workers within the radiotherapy space.
Conclusion: The challenges identified in this review are common among all the geographical regions in the African continent. Therefore, all institutions offering radiotherapy education and training programs, management of the medical centers for radiotherapy and oncology, national and regional professional bodies for medical physics, ministries of health, governments, and relevant stakeholders must take keen interest and work together to achieve this goal.

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1. Introduction

Radiotherapy involves the use of ionizing radiation (e.g., photons, electrons, and protons) beams to treat cancer. A series of procedures make up the therapy process including; disease diagnosis, dose prescription, treatment simulation, planning, plan review, beam delivery, and patient follow-up [1]. Nearly 50% of cancer patients worldwide require radiotherapy at some point during their cancer journey, making it an essential part of cancer treatment [2]. There are various machine types that can be used to deliver radiotherapy, including brachytherapy equipment, kilovoltage machines, and external beam high-energy radiation machines [3]. When combined with surgery or chemotherapy, radiotherapy can both treat and eliminate tumors; additionally, it can ease the suffering of people with terminal cancer (i.e., palliation) [4,5].

However, radiotherapy workflow involves many complex tasks, including tumor and organ segmentation, dose optimization, outcome prediction, and quality assurance (QA), which can be very complex and time-consuming potentially affecting the quality of treatment outcomes [6,7] coupled with the global rising burden of cancer [8]. For instance, skin motion in relation to internal anatomy can limit reproducibility and induce systematic setup errors. Also, the process of organ delineation may further induce a systematic error during treatment planning [9]. Moreover, patient-specific quality assurance requires a lot of time, which may result in machine downtime and interfere with patient care [10].

Innovations in treatment technology are desperately needed given the rising incidence of cancer worldwide and the significant discrepancies in radiotherapy services [11]. Artificial intelligence (AI) technology has been suggested as a method to improve the standardization, speed, and quality of radiotherapy workflow, ultimately resulting in more precise and safe radiation administration through automation. Machine learning (ML) and deep learning (DL) are subdomains of AI, which is defined as a set of algorithms that execute tasks connected with human thinking or intelligence [6]. The tasks that typically require human intelligence, such as visual perception, pattern recognition, decision-making, and problem-solving, are carried out at a similar or higher level of performance by means of the development and application of complex computer algorithms [7]. Deep learning has the ability to automatically extract features from huge amounts of data. Additionally, deep learning may uncover details in images that the human eye is unable to see, which is crucial for the early identification of malignancies using image data [12]. On the other hand, machine learning focuses on developing predictions by utilizing mathematical algorithms to find patterns in data. For instance, automated actions can be performed by machine learning algorithms using patient data to help in the identification and diagnosis of cancer [13].

It is recommended that commissioning, clinical implementation, and then daily use of the AI models together with model- and case-specific Quality Assurance (QA) are in place before successfully integrating AI technology into clinical practice [6]. The commissioning process uses a large amount of data to train an AI model, after which the accuracy of the model and reproducibility is evaluated, verified, and implemented. To guarantee the safe and clinically appropriate use of a model, a multidisciplinary team who have adequate knowledge of machine learning and deep learning models must be engaged prior to clinical implementation [6]. This implies that all staff participating in radiotherapy processes, such as radiation oncologists, medical physicists, radiation therapists, IT specialists, etc., must have completed some sort of basic education or training in AI machine learning and deep learning techniques.

Each member of the radiotherapy professional team, notably the medical physicist, must develop an attitude of knowledge sharing and collaboration in the application of AI in radiotherapy practice. This would increase the capacity of medical physicists to be able to evaluate the strengths and weaknesses of AI technology, produce high-quality automatic treatment plans using machine and deep learning-based methods, identify issues with QA measurement, and establish proactive measures [14]. The absence of these requirements could limit or prevent the full implementation of the technology into clinical practice. In order to assess the readiness of Africa for the integration of AI technology into radiotherapy practice, we will highlight the current status and challenges facing radiotherapy services in Africa, discuss the applications of AI technology in radiotherapy, and how AI would improve radiotherapy services in Africa. Similar analysis has been carried out for medical imaging, which is closely related to radiotherapy [15].

2. Radiotherapy services in Africa

The development of radiotherapy began following the discovery of x-rays in 1895 and radioactivity in 1896. A few months after its discovery, X-rays were used for the first time to treat cancer [6]. Megavoltage therapy and brachytherapy standard operating procedures were developed through scientific advancements, trial and error, and technological developments. With the introduction of the Cobalt-60 machine and the medical linear accelerator in the 1950 s, megavoltage therapy reached its peak [17].

Africa's involvement with radiotherapy dates back to 1929 in North Africa when Morocco opened the Bergonié Center at Casablanca's Averroes Hospital. Later in 1930, Egypt's Kasr Al-Ainy Hospital (Cairo University Hospital) built its first radiotherapy department [16]. In North Africa, 145 megavoltage radiotherapy machines (MVM) across 85 centers have been documented. Of the total, Cobalt-60 units make up 31% (45 units) whiles 69% (100 machines) are linear accelerators. In addition, to the megavoltage machines (MVMs), there are 36 brachytherapy after-loading devices in the region. As of February 2012, there were 74 MVMs in Egypt, 30 in Morocco, 19 in Algeria, 15 in Tunisia, and 7 in Libya. The population that one MV machine can serve varies between these countries. For example, in Tunisia and Algeria, there were 1.36 and 0.54 MV machines per million respectively. Also, in Egypt, Libya, and Morocco, there were 0.9, 1.29, and 0.9 MV machines per million respectively [4].

In 1969, the Lagos University Teaching Hospital (LUTH), Nigeria became the first facility in West Africa to purchase a cobalt-60 teletherapy machine [18]. Later in the mid-1970 s, MVMs were also commissioned in Liberia, Senegal in 1989, Ghana in 1997, Mauritania in 2010, Mali in 2012, and Côte d'Ivoire in 2018, while the rest of the West African countries had no history of external beam radiotherapy services [19]. Over the past five decades, Western African countries have seen a surge in the total number of MVMs and per-capita radiation capacity. As of 2019, Nigeria recorded the highest number (i.e., nine) of the 22 MVMs followed by Ghana (five), Senegal (three), Cote d'Ivoire (two), Mauritania (two), and Mali (one) [19].

Also, the beginning of radiotherapy-assisted cancer treatment in East Africa was reported in the 1970 s when a Cobalt-60 EBRT treatment system was supplied to Kenyatta National Hospital by the Karolinska Institute as part of a Swedish and Kenyan government collaboration [20]. In central Africa, work on a radiation facility in Zambia's capital city of Lusaka's University Teaching Hospital began in 2003. Zambia's 13 million residents did not have access to radiotherapy until 2006 [21]. Also, the plan for the first modern radiotherapy cancer center in Rwanda was established in 2016 and later became operationalized in 2019 [22]. By 1994, one Cobalt-60 machine and three linear accelerators, and five high-dose-rate after-loading brachytherapy systems were distributed across South Africa. Twenty thousand cases were treated annually by fifty-eight therapists and one hundred and ninety therapy radiographers [23].

The population served by each MVM is a critical factor in deciding the radiation services provided by countries. 1 MVM is what the IAEA advises for every 250,000 people. None of the 54 nations in Africa is able to satisfy this recommendation. Even Mauritius which is known to have the lowest population-to-MVM has failed to satisfy this recommendation [24]. In 2015, with an estimated 1.2 billion people, Africa only possessed 394 teletherapy units. Of those, 376 were megavoltage units. There were 3 million patients per treatment unit that had access to radiotherapy technology [25]. External beam (EB) radiotherapy was accessible in 25 of the 54 countries in Africa. The majority of the MV capacity (i.e., 57%, or 209/364) was located in Egypt and South Africa [26]. While LINAC-based radiation therapy facilities are available in 28 African nations, there are sadly none at all in the remaining 27 nations. South Africa (97) and the Mediterranean nations (227) are where you can find the majority of LINACs in Africa. In the 28 nations having LINAC-based radiation therapy facilities, there is one machine each for every 423 000 people, nearly 5 million people in Kenya, and more than 100 million people in Ethiopia. One radiation therapy equipment is used for every 87,000, 119,000, 134,000, and 195,000 individuals in HICs including the USA, Switzerland, Canada, and the UK respectively. The number of machines to people in Africa is one LINAC per 3,000,000 people [27]. In middle Africa with a total of 100 machines, the number of radiotherapy machines per million people is 0.078, which is below the recommendation of 1 [28].

On the other hand, less than half of the African countries (i.e., 22 of the 54) have access to brachytherapy services [29]. Cervical cancer, a tumor with a very high prevalence in the continent of Africa, is mostly treated with brachytherapy as an intracavitary procedure. Due to reduced treatment times, high-dose-rate brachytherapy (HDR) is recommended for facilities treating a large number of patients. Although Sievert first proposed the idea of remote after-loading in 1937 to reduce radiation exposure to workers, a couple of countries, mainly in sub-Saharan Africa, still use manual after-loading techniques today. Africa is yet to have access to electronic brachytherapy [25]. Fig. 1 shows a map comparing the total number of equipment (i.e., radiotherapy (RT) and brachytherapy (BT)) per million population in Africa, Western Europe and North America.

As of March 2020, there were 430 megavoltage units in total scattered unevenly over the African continent with the majority in the Northern and Southern parts. Of the 54 African countries, 28 (52%) had external beam radiation accessible, with the majority of the installed units in Egypt (119 units) and South Africa (97 units). Cobalt-60 units and linear accelerators are both present in 50% of all countries. Only linear accelerators are used in 11 (20%) countries, and only cobalt-60 units are used in three (11%) [28,30]. In 2030, it is anticipated that between 1500 and 2000 MV units and about 350 brachytherapy after-loaders will be required, depending on the pace of radiation use and patient throughput [26]. Table 1 shows details of current data on radiotherapy resources for patient treatment in 33 African Countries [31].

3. Current challenges of radiotherapy delivery in Africa

Table 2 shows a summary of the main challenges faced by radiotherapy facilities in Africa. It is challenging for cancer patients to receive the care they require in Africa due to inadequate radiotherapy equipment, limited human resources, insufficient education/training of radiotherapy personnel, and lack of innovation in treatment technology [11]. As of 2014, Senegal, for instance, had 3 Medical Physicists and 2 Radiation Oncologists. This radiation team sees 50 patients each day, of which 40% have cervical cancer [29]. Also, Ethiopia currently has only one operational cobalt teletherapy equipment that serves more than 100 million people and treats more than 1,700 radiotherapy patients annually [32]. According to Stefan's investigation of the resources available for childhood cancer in Africa, there are several difficulties in providing care for children with cancer. These include a lack of clear therapy protocols, inadequate radiation facilities and staff, poor personnel education or training, and a lack of research time [33].

African nations with zero Oncologists include Lesotho, Benin, Gambia, South Sudan, and Sierra Leone. On the contrary, Malawi, Burkina Faso, Rwanda, and Togo each have one oncologist, and Egypt has up to 1,500. This results in an extremely high caseload for each radiation therapist [34]. Sub-Saharan Africa needs at least 2000 radiation oncologists and 1250 medical physicists, which is almost ten times more than what is already available, due to the high cancer prevalence [4]. According to the IAEA, a basic radiotherapy clinic with one MV unit should contain seven radiotherapy treatment teams, three to four medical physicists, and at least four to five radiation oncologists. Many of the centers in this area fare poorly in comparison to this standard. The IAEA also suggests one medical physicist for every 400 new patients and

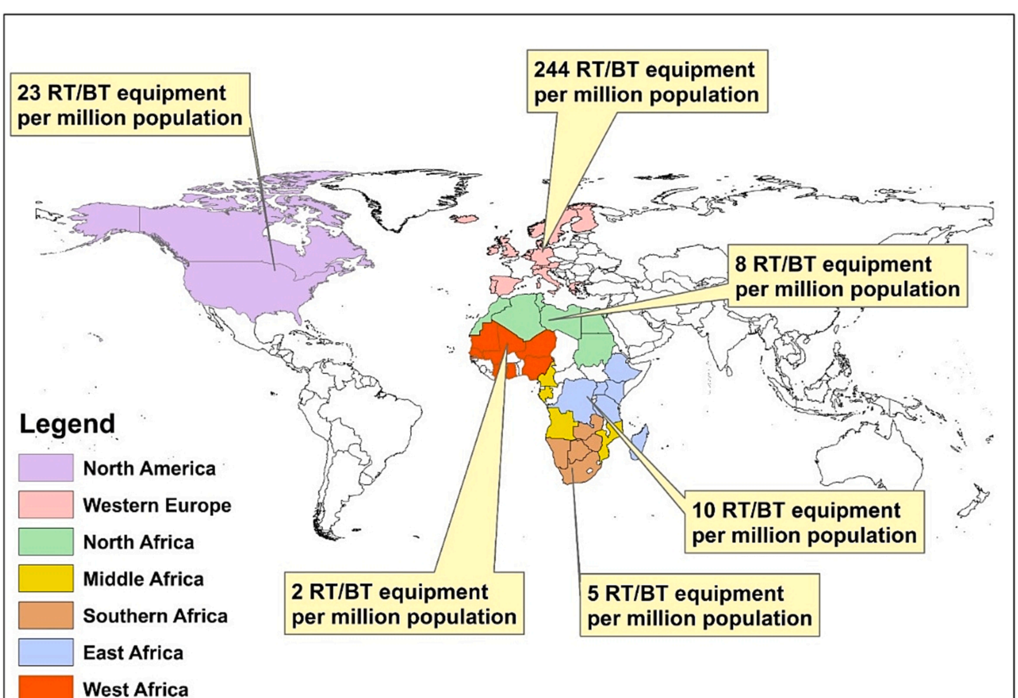

Fig. 1. Radiotherapy and Brachytherapy equipment per million population in Africa, Western Europe and North America.

Table 1
Current status of radiotherapy resources in 33 African countries [31].

S/N	Country	Region Name	RT Centers	MV Therapy	Proton Ion Therapy	Xray (kV) Therapy	Brachy Therapy Inc El	Total number of equipment per million of population	Last Update
1	Algeria	North Africa	16	37	0	0	12	1.12	2020
2	Angola	Middle Africa	2	3	0	0	1	0.12	2023
3	Botswana	Southern Africa	1	1	0	0	1	0.85	2022
4	Burkina Faso	West Africa	1	1	0	0	0	0.05	2021
5	Cameroon	Middle Africa	3	2	0	0	0	0.08	2022
6	Cote D'Ivoire	West Africa	1	2	0	0	0	0.08	2019
7	DR Congo	East Africa	1	1	0	0	0	0.01	2021
8	Egypt	North Africa	75	120	0	1	23	1.41	2022
9	Ethiopia	East Africa	3	3	0	0	1	0.03	2022
10	Gabon	Middle Africa	1	2	0	0	0	0.90	2018
11	Ghana	West Africa	3	6	0	0	3	0.29	2022
12	Kenya	East Africa	10	17	0	0	5	0.41	2022
13	Libya	North Africa	5	8	0	0	0	1.16	2022
14	Madagascar	East Africa	2	3	0	0	1	0.14	2022
15	Mali	West Africa	1	1	0	0	0	0.05	2019
16	Mauritania	West Africa	1	3	0	0	1	0.86	2019
17	Mauritius	East Africa	1	3	0	0	1	3.15	2019
18	Morocco	North Africa	30	46	0	0	10	1.52	2022
19	Mozambique	Southern Africa	1	1	0	0	0	0.03	2020
20	Namibia	Southern Africa	2	2	0	0	1	1.18	2022
21	Niger	West Africa	1	1	0	0	0	0.04	2021
22	Nigeria	West Africa	7	9	0	0	2	0.05	2022
23	Reunion	East Africa	1	5	0	0	0	5.58	2018
24	Rwanda	East Africa	1	2	0	0	0	0.15	2021
25	Senegal	West Africa	2	2	0	0	1	0.18	2022
26	South Africa	Southern Africa	62	103	0	8	23	2.26	2022
27	Sudan	North Africa	4	6	0	0	0	0.14	2022
28	Tanzania	East Africa	4	8	0	0	4	0.20	2022
29	Togo	West Africa	1	1	0	0	0	0.12	2022
30	Tunisia	North Africa	14	26	0	1	4	2.62	2022
31	Uganda	East Africa	1	3	0	0	1	0.09	2022
32	Zambia	Southern Africa	1	3	0	0	2	0.27	2019
33	Zimbabwe	Southern Africa	3	1	0	0	2	0.20	2022

one radiation oncologist for every 200–250 new patients treated annually [4].

The Lancet Oncology issued a Report in 2015 on improving access to radiation worldwide. The report indicated that many low- and middle-income countries (LMICs) lacked adequate radiotherapy coverage and predicted that by 2035, there would be a need for 2,600 radiotherapy departments, 5,200 machines, and 55,800 radiation oncologists, medical physicists, and radiotherapy technologists to meet the demand [35]. With less than one external beam of radiotherapy equipment per million people across the continent, Africa has the least developed radiotherapy capacity when compared to North America, which has roughly 15 machines per million people [28]. In Africa, this discrepancy is particularly obvious, with only 25% of the need being addressed and 29 of the 54 countries lacking a functioning radiation facility [36]. The discrepancy is also stark in sub-Saharan Africa (excluding southern Africa), where there are ten times fewer radiotherapy machines per million people than in North America. It is predicted that 700 more radiotherapy machines will be required to bring Africa's capacity up to par. The incidence of cancer is expected to double in Africa's less-resourced regions by 2040, which will only increase the need for these services [32].

Finance is one of the key issues limiting the development of radiation services in Africa. A sizable portion of the cost of administering radiotherapy is made up of supplies like teletherapy machines, brachytherapy after loaders, and the necessary ancillary items like planning software and radioactive isotopes, as well as labor costs like those of oncologists, medical physicists, radiation therapists, and nurses [11]. In wealthy countries, it is impossible to estimate the price of putting together an AI/ML-based healthcare solution. However, it might cost as little as $6,000 for basic chatbots or as much as millions of dollars. The collecting and preparation of data, the use of hardware and computational resources, and the upkeep and improvement of systems all have costs connected with their use or adoption of the technology [37]. This high cost makes it challenging for most African countries to either expand existing or create new facilities. The small number of radiotherapy facilities that patients overwhelm reduces the efficiency and effectiveness of quality assurance programs implementation [34,38]. The implementation of quality assurance in radiation treatment is particularly difficult in low- and middle-income countries because of a lack of staff training, a lack of national norms, a lack of quality assurance tools, and a high patient throughput each day [39].

It has been established that Africa's radiation staff are in need of more and better training programs. Sub-Saharan African nations with well-established training programs include Tanzania, Zimbabwe, Ghana, South Africa, Egypt, Morocco, and Zambia, with the majority of nations reliant on outside training. The intended results of increased human resource self-sufficiency have not been achieved by sending trainees to other continents since trained professionals are less likely to return to their place of origin after training and are more likely to stay where they have been taught. This is probably due to a lack of efficient staff retention programs and inadequately equipped Centers that do not correspond to the knowledge that staff trained in well-equipped facilities should apply [40]. Insufficient clinical and/or radiation oncology training programs are a significant barrier to addressing the shortage of radiotherapy staff in Africa [28].

The applications of data science are still relatively underdeveloped in Africa given the fact that the development of AI models for radiotherapy

Table 2
Summary Chart of major challenges radiotherapy faces in 33 African countries.

Countries	Less than one piece of RT equipment per million population	No AI radiotherapy education curriculum	Lack of human resources with sufficient training or expertise	Countries with inadequate/ unreliable funding sources	Insufficient data for training AI models/ lack of AI technology and resources
Algeria		+		+	+
Angola	+	+			+
Botswana	+	+	+		+
Burkina Faso	+	+		+	+
Cameroon	+	+	+	+	+
Cote D'Ivoire	+	+		+	+
D. R. Congo	+	+		+	+
Egypt		+	+	+	+
Ethiopia	+	+		+	+
Gabon	+	+		+	+
Ghana	+	+	+	+	+
Kenya	+	+		+	+
Libya		+	+	+	+
Madagascar	+	+		+	+
Mali	+	+		+	+
Mauritania	+	+		+	+
Mauritius		+	+	+	+
Morocco		+		+	+
Mozambique	+	+		+	+
Namibia		+		+	+
Niger	+	+		+	+
Nigeria	+	+	+	+	+
Reunion (France)		+		+	+
Rwanda	+	+	+	+	+
Senegal	+	+	+	+	+
South Africa		+	+	+	+
Sudan	+	+	+	+	+
Tanzania	+	+	+	+	+
Togo	+	+		+	+
Tunisia		+		+	+
Uganda	+	+	+	+	+
Zambia	+	+		+	+
Zimbabwe	+	+		+	+

practice requires a large volume of specific trainable data sets [37]. This is especially true for datasets with labels, which must be annotated by physicians or other medical professionals and are therefore expensive and time-consuming to gather. Due to the low adoption of electronic medical records and digitization in Africa, there are few locally generated useful data that are crucial for creating AI systems [41]. In addition to data volume and quality, Africa also lacks professionals in AI technology. A lack of infrastructure and resources for education may prevent some African countries from importing AI professionals or teaching AI to their own populace. Thus, it's possible that only a select group of wealthy people will be able to access this knowledge, worsening inequality.

Many nations are currently working to create a governance policy or legislative framework to support the use of AI in many industries. There are no regulations governing who is responsible for unfavorable results that may arise from the use of artificial intelligence in healthcare, which is highly probable given how and where AI may be implemented. However, some situations and places are not foreseen or covered by the current legislation, making such resolutions less likely to involve the application of the law. In many African nations, this will have legal repercussions for users and patients [41].

4. Overview of AI applications in radiotherapy

Artificial intelligence has gained recognition in radiotherapy practice because most of the processes in the radiotherapy chain involve computer medical image processing, calculation, and hardware control. With the help of big data processing and high-performance computing, AI technology can be used to automate and perform numerous tasks throughout the entire workflow of radiotherapy, beginning with the selection of the best radiation method, such as choosing between proton and photon radiation to treatment planning, plan evaluation and quality assurance, dose delivery, and patient care [1,42]. For example, a Clinical Decision Support System (CDSS) based on deep learning technology was created by Liang et al. [12] to provide cancer therapy alternatives by extracting and analyzing a significant amount of clinical data from medical records. The study showed that by learning from clinical big data of cancer patients, deep learning can assist doctors in selecting the optimal treatment option and eventually enhance cancer patient treatment plans [12].

Radiation treatment planning begins with precise segmentation of organs at risk (OARs) and target volumes. Deep learning convolutional neural network (CNN)-based auto-segmentation models have recently been demonstrated to increase this process' consistency and effectiveness. Based on characteristics of the position and intensity of the voxel and neighboring voxels, these models typically categorize every voxel in an image as belonging to an OAR or target [6]. Similarly, Machine learning CNNs have been used to perform automatic segmentation of radiation targets and OARs [42]. AI technology has been exceptional in the segmentation of different structures during the treatment planning stage [12,43–47].

During the treatment planning stage, a 3D-dose distribution of a plan is usually generated utilizing a variety of techniques (e.g., convolution-superposition algorithm and Monte Carlo simulation) which can be tedious and time-consuming [1]. To expedite optimization or establish the best achievable dose distribution from the patient image, DL can forecast the dose distribution from radiation therapy treatment [42]. The distribution of the desired target dose conformity and adequate sparing of critical structures from the treatment plan is mostly achieved with the use of knowledge-based dose volume histograms (DVHs) [14]. Many human factors, including the selection of radiation beam angles and the plan's optimization parameters, affect the quality of the dose distribution plans [7]. The dose distribution index (DDI) variable, which offers dosimetric estimates on the target coverage, organs at risk, and healthy tissue in the treated organ, is used to assess the quality of a treatment plan. With the aid of AI, the DDI value is predicted using machine learning from the DVHs [1]. Data-based regression analysis is used as the dose-volume histogram (DVH) estimate algorithm to create a knowledge-based planning (KBP) model from a previous, clinically approved treatment plan [48]. The application of machine learning to knowledge-based DVH techniques has shown promising outcomes in the treatment planning of head and neck, pancreas, and prostate cancers [49–52].

Prior to treatment, target delineations, which call for image registration, are performed using multimodal and four-dimensional imaging modalities. Image registration is the process of identifying geometric correspondences between two or more imaging data sets that differ in time, place, modality or subject [53]. Deep learning AI algorithms have the ability to immediately discover the best attributes for registration from the input data. Using a twelve-element output vector modified from 2-dimensional (2D) DenseNet, the affine image registration deep learning model was successfully used to predict transformation parameters and register three-dimesional (3D) images. An encoder was initially applied to the image pair to extract features. Many fully connected layers were then concatenated using the attributes as input, and regression was utilized to complete the registration process [54]. In a similar vein, CNNs are regarded as the most effective and potent deep-learning techniques for medical image registration. Researchers have had modest success in registering chest computed tomography (CT) images, brain CT and MR images, 2D X-ray images, and 3D CT images using CNN deep learning algorithms [55].

AI can create effective motion management models that take motion variability into consideration, including magnitude, amplitude, frequency, and other factors. These models can forecast respiratory movements using information obtained from outside surrogate makers [56]. If motion management techniques are not used, patient or internal organ motion during RT treatment may increase the dose administered to non-target tissues. AI can be utilized to create dynamic motion management models that are customized to a patient, which can enhance tumor tracking and halt radiation delivery to insufficient target places. To precisely measure and anticipate the tumor position in advance, AI algorithms could automatically adapt to intricate breathing patterns in real-time [57]. Motion during treatment planning and dose delivery is most notable either in tumor expansion or contraction as well as anatomical variations that might affect the doses delivered to the tumor and other organs. In such cases, it is necessary to re-plan treatment (also referred to as adaptive treatment) in light of the most recent images of the patient's anatomy. AI may offer tools to forecast which patients need treatment adaption and the appropriate interval during which it should take place [7]. For instance, when a patient receives radiation therapy, ML can spot major alterations in their anatomy and foretell which of their cases would benefit from adaptive radiotherapy [42].

In every radiotherapy department, the medical physicist is mainly responsible for performing quality assurance tasks. Quality assurance (QA) is used to check and keep an eye on the tools and processes used in diagnosis and treatment, as well as the clinical support systems. AI can be used to carry out automated quality checks (QCs) that, if done manually, would not be viable on a regular basis due to the time commitment [42]. There are two major types of QA in radiotherapy namely; machine and patient-specific QA [14]. Machine quality assurance involves evaluating the capabilities of various radiation medical devices (e.g., linear accelerators, electronic portal imaging systems, onboard imaging, and computed tomography CT) [10]. The abundance of information gathered during these evaluations has made it possible to create AI algorithms that can predict trends and errors, like multi-leaf collimator positioning errors and trends in beam symmetry, as well as automatically identify imaging artifacts. These techniques might make the QA process more effective, giving medical physicists more time for other tasks [7]. Commissioning and quality assurance (QA) for linear accelerators (linacs) need a lot of work and time. Machine learning can be used to lessen the workload associated with linac commissioning. A machine learning system can be trained using previously obtained beam data to simulate the inherent correlation of beam data under various configurations. The trained model is thus able to produce accurate and dependable beam data for linac commissioning for routine radiotherapy [56].

Patient-specific QA activities include dosimetric measurements of treatment plans, in vivo dosimetry, and monitor units [14]. For extremely complex treatment plans, a dosimeter-containing phantom is used to physically measure the delivered dose, which is then compared to the intended dose. The vast majority of plans succeed in this QA stage, but in the rare instance where a plan is unsuccessful, numerous potential contributing causes necessitate examination, which could postpone treatment. In order to forecast QA passing rates based on the treatment plan itself and to pinpoint probable mistake sources, an AI system has been developed, which may eventually replace the necessity for physical dose measurements [10].

5. How ready is Africa for the introduction of AI in radiotherapy?

It may not be an easy task to implement and integrate AI technology into clinical practice across radiation centers in Africa. This is because, prior to integrating the technology into clinical practice, challenges of AI technology must be overcome and recommendations for the integration must be met. The process will necessitate an initial significant time and massive resource investment, as well as efforts to comprehend the benefits and constraints of the technology [7].

Regular QA is strongly recommended after the successful implementation of any AI-based program [6]. The adoption of AI in clinical practice necessitates the establishment of a Quality Management Program (QMP) to ensure that the QA model hasn't been accidentally changed and that it is still valid after a (small) software upgrade. For this use, a reference data collection that reflects clinical practice should be chosen at the time of commissioning. The reference dataset should be forecasted again on a frequent basis and compared to the initial predictions during commissioning (end-to-end performance) to ensure model consistency and identify changes in the workflow [6].

Large datasets are mostly required to train, validate, and test many AI learning models, especially when deep learning (DL) algorithms are employed. Depending on the task (i.e., training, validation, and testing) that must be performed, AI models are either developed in-house, in partnership with a vendor, or already commercially accessible [6,14]. Using deep learning algorithms, like CNN, requires hundreds of millions of trainable data [57]. For these algorithms to be used safely, high-quality data are required for training [58]. The data needs to receive expert validation and broad acceptance from the computer science and medical radiation science communities [59]. It is advisable to use locally acquired input data in order that the department's clinical guidelines and imaging methods are preserved [6]. This can be achieved by establishing an open-access national data bank to accelerate the development of AI models [60]. The data may need to be triaged after it has been evaluated to ensure that it is a curated representation of the patient population and clinical practice under consideration [6]. However, these datasets are either frequently unavailable, ridiculously expensive, or legally restricted [55]. It is not recommended to generalize data from developed countries to underdeveloped ones without anticipating differences. Therefore, the best course of action appears to be to ensure equity in data representation while taking into account the geographic variances in diseases, demographics, and health services [57].

With regard to who “owns” the data and who has the right to use it, particularly where it has a commercial value, the requirement of huge amounts of data for the deployment of AI technology in radiotherapy practice may pose legal and ethical questions. Although obtaining patient agreement for data use would be ideal, it may not be possible given the enormous number of patients in large datasets, especially in retrospective contexts [61]. The application of existing laws may be one of the most likely solutions to overcoming legal issues [41]. The laws should be able to address issues of ownership and rights of the use of data. If the use of existing laws cannot address the legal issues, new laws can be unanimously developed by the various government in the African continent to address legal problems that may occur due to a breach of security and privacy [62]. In the meantime, anonymizing patient data must be mandatory to protect patient privacy while attempting to maximize the utility of the data.

To the best of our knowledge, no AI models based on public databases with radiological images have been developed using deep learning in Africa [63]. Even if such models exist, they might not be totally validated. A preliminary search in five electronic databases to identify AI tools created between January 2000 and January 2022 utilizing patient cohorts in Africa revealed 12 prediction tools for various cancers and uses. Unfortunately, they have not been validated for predicting cancer outcomes in about 90% of African nations and their subsequent implementation in radiotherapy practice [64]. The absence of AI models is due to the lack of sufficient radiological images (or data) needed to successfully train the deep learning algorithm [63]. In the meantime, the challenges with limited data could be overcome with the use of a data augmentation approach, which has the potential to increase the amount of usable data by adding affine image transformations to the original image sets during the data training for auto-segmentation [14].

The integration of AI with radiation practice has frequently been led by medical physicists. AI can support knowledge-based treatment planning in the radiotherapy process with minimum input from the medical physicist [14]. It is advised that AI content be included in the curriculum for training and educating aspiring medical physicists at all academic institutions providing such training across Africa [63]. In Europe for instance, the core curriculum for training medical physics students both at undergraduate and graduate levels in radiotherapy has been developed to include AI. The curriculum which has been implemented at all institutions’ training medical physicists has been endorsed by thirty-two European Medical Physics Societies [65]. Therefore, the curriculum for the education and training of radiotherapy personnel in Africa must be revised to meet the recommendations of international standards. This might fill the widening teaching gap throughout the continent, personalize and sustain learning, and provide individuals with a way to upskill for the changing digital future.

A study conducted by Ige et. al (2020) revealed that the curriculum for formal education and training programs in radiotherapy is not standardized across Africa. Also, there are not many higher education options in fields relevant to radiotherapy. The available radiotherapy-related programs are mainly academic, with little clinical content [27]. The absence of AI radiotherapy courses in the current curriculums may be due to a limited number of no qualified professionals capable of teaching and supervising AI-related courses [4]. Since the majority of the staff in a radiotherapy department are radiation oncologists, medical physicists, and radiation therapists [4], a crucial first step in preparing radiation therapists, medical physicists, and radiation oncologists to use therapeutic technology in a competent and safe manner may be to incorporate AI and ML principles into radiation therapy education [66]. The education and training of radiotherapy personnel would however require a collaboration of African institutions and radiotherapy departments to collaborate with relevant international bodies and stakeholders. It is necessary to make a deliberate effort to enhance cancer education in medical schools. There are helpful guides regarding curricular content, such as the International Union Against Cancer’s Ideal curriculum in oncology for medical students [67].

6. Role of international institutions/bodies

The Federation of African Medical Physics Organizations (FAMPO), established in 2009, is the regional federation of the International Organization for Medical Physics (IOMP) in Africa. The Federation promotes growth and development of medical physics in Africa. As of 2016, Tabakov (2016) had reported a total number of 700 medical physicists in Africa [68]. Ige et al. [27] in 2020 estimated the number of medical physicists in Africa to be 1,041, nearly 50% increase in the 2016 figure. Most clinical medical physicists in Africa are radiotherapy-based, with large inadequacy of personnel in medical imaging [69]. Since its establishment, FAMPO has been actively promoting the development of personnel and practice of medical physics in the region [70,71]. The first FAMPO Conference, organized by the Association of Medical Physicists in Morocco, and held from 10 to 12 November 2023 in Marrakech, Morocco, brought together over 300 participants.

In addition to FAMPO’s contribution, agencies like International Atomic Energy Agency (IAEA), International Centre for Theoretical Physics (ICTP), International Organization for Medical Physics (IOMP) have played very important roles towards development of the profession and its practice in the region.

The IAEA provides important programs for about 176 nations, including low-and-middle-income countries, to help them use nuclear technology peacefully. There are 45 IAEA member states that take part in these programs in the Africa region. Through its programmes and projects, the IAEA has supported highly the development of radiation medicine services, capacity building, education and training, technical assistance, etc. The education and training activities cover a variety of nuclear-related subjects through in-person training sessions, workshops,

Table 3
IAEA coverage in Africa [72–75].

Project Code	Project Title	Project Objective
RAF6051	Strengthening Education and Human Resources Development for Expansion and Sustainability of Nuclear Medicine Services in Africa	To strengthen and sustain nuclear medicine capabilities in Africa through academic education programmes
RAF6054	Strengthening and Improving Radiopharmacy Services	To improve good operating standards and pharmaceutical regulation of hospital preparation of radiopharmaceuticals in order to expand the range of safe and effective radiopharmaceuticals available in African Member States and improve patient safety in nuclear medicine practice
RAF6055	Improving the Quality of Radiotherapy in the Treatment of Frequently Occurring Cancers	To enhance the quality of the delivery of radiotherapy services in AFRA MS through harmonized clinical training schemes and sensitization of policy makers
RAF6056	Supporting Human Resources Development in Radiation Medicine	To strengthen the treatment of cancer through the training and education of radiation medicine professionals in AFRA States
RAF6057	Strengthening the Quality of Nuclear Medicine Services	To enhance the quality of the delivery of nuclear medicine in AFRA States through a well-established quality management system.
RAF6058	Strengthening the Capacities for Radiopharmacy and Medical Physics and Radiology for Expansion and Sustainability of Medical Imaging Services	To strengthen and sustain imaging services in Africa through academic education programmes (radiopharmacy) and training as well as effective diagnostic and interventional radiological practices

online learning, fellowship programs, and schools [24,72]. Some projects on radiation medicine being run by IAEA in collaboration with its Member States in Africa are presented in Table 3.

The International Center for Theoretical Physics (ICTP) has also contributed significantly towards the education and training of clinical medical physicists at the master's degree level. The program is co-sponsored by IAEA and supported by recognized international organizations. The organizations include the International Organization for Medical Physics (IOMP), the European Federation of Organizations in Medical Physics (EFOMP), and the Italian Association of Medical Physics (AIFM) [72]. In the last 3 decades, ICTP's College on Medical Physics and training courses have successfully trained over 1,000 medical physicists in about 100 low-and-middle-income countries [76].

As a result, all radiotherapy departments, educational institutions that train students towards providing radiotherapy services, and relevant stakeholders in Africa must take a strong interest and make an earnest effort in collaborating with IAEA, international educational institutions and organizations, manufacturers of radiotherapy equipment, and developers of treatment planning software to achieve this goal.

Under its new Harnessing Data Science for Health Discovery and Innovation in Africa program, the National Institutes of Health in the United States has committed approximately $74.5 million over five years to advancing data science, accelerating innovation, and promoting health discoveries throughout Africa. Given these resources and investments, AI/ML applications' influence on healthcare in Sub-Sahara African (SSA) is possible [37,60]. To speed up the integration of AI technology in radiotherapy practice, African countries must invest heavily in skills, infrastructure (i.e., data centers), and technologies such as electronic health records and cloud storage to meet up with the data required for training DL and ML algorithms. Cloud-based technology can be used as a tool to speed up peer review by offering a platform for the private distribution of planning data sets between radiation centers for external assessment and input. The utilization of such platforms for training and education as well as reporting, learning and assessment in radiotherapy practices can also make it easier for people to take part in international clinical studies, such as those that are managed by the International Atomic Energy Agency [77–79].

During the peak of the COVID-19 pandemic, several international collaborations between countries, institutions and individuals were established to develop remedial actions and mechanisms in the fight against the disease [80–83]. The period saw a boom in research output towards AI applications for diagnosis and treatment of cancer cases [84–86].

7. How AI can improve radiotherapy services in Africa

The structural issues such as the shortage of staffing in most radiotherapy facilities in Africa that lead to inconsistent patient results would be overcome when AI technology is implemented. The workflow of radiation treatment is time-consuming due to the numerous manual inputs involving the medical physicist, radiation oncologist, dosimetrist, and radiation therapist [13]. Hence, when implemented, the technology will augment the limited staff across Africa by reducing their workloads and allowing them to spend more time with patients and providing actual patient care.

One of the most important stages that can take a lot of time during treatment planning is the contouring of malignancies and the healthy organs surrounding them. There are no specific guidelines for contouring medical images due to the variety of anatomical organ characteristics [77]. To satisfy the demand for treatment in clinics with limited resources and staffing shortages, AI could be used to automate image analysis to help radiation therapists, oncologists, and medical physicists expedite the contouring of several image portions in a single session within a fraction of the time. Additionally, AI might be able to assist the radiation team in navigating the challenges posed by the physiological diversity of anatomical structures during image interpretation [44,77]. In particular, for new radiotherapy practitioners who are just starting out and may not have the full radiological education and expertise in radiotherapy operations, the application of AI based on machine learning algorithms for image analysis could be helpful in their day-to-day work [44,77].

The adoption of AI technology in clinical practice will encourage radiotherapy professionals to place a priority on continuing their education in the field of machine and deep learning while potentially improving their abilities in manual segmentation and organ contouring. Knowledge and applications of AI models in radiotherapy practice would significantly reduce staff workload as the majority of the staff's work will also be focused on macro-processes, such as assessing the equipment performance quality [56]. Medical physicists are those who are mainly responsible for overseeing the status of equipment performance in Africa through QA checks. For example, for patient alignment and motion management, medical physicists must make sure that the performance quality of radiotherapy machines and equipment is of high precision and within tolerance levels [37]. Both machine learning and deep learning techniques will assist medical physicists in better identifying QA measurement problems and developing proactive QA strategies [13]. Also, the notion that radiotherapy services are not widely accessible in Africa is not entirely due to the high base cost of the equipment but rather the large load of maintenance costs when a radiotherapy machine breaks down. The likelihood that a piece of equipment will continue to operate is frequently affected by recurring high service and maintenance costs [34]. Annual recurrent costs, which include maintenance and source replacement, can be in the range of 5% and 15% of the initial capital investment [10]. Through quality assurance, AI technology when implemented would save maintenance costs due to the ability of the technology to identify and resolve inefficiencies.

African oncologists were considering using AI-based models to predict outcomes for patients with breast, cervical, and colorectal carcinomas [63]. This roughly corresponds to the prevalence of malignant neoplasms across the continent, with the five most prevalent subtypes being breast, cervical, prostate, liver, and colorectal cancers. However, no actionable AI patient-based platforms have been suggested to make it easier to screen for, identify, and treat prostatic and hepatocellular cancer in the area. So, research aiming to suggest new platforms and/or external validation of current AI-based platforms, especially for liver and prostate cancer as well as other, hitherto unconsidered malignancies, will be beneficial for Africa [63].

8. The role of medical physicists in radiotherapy services and AI applications

In the history of radiotherapy service delivery, Medical Physicists have always played a major role when it comes to developing CT-based dose calculation, treatment planning, image-guided radiation therapy, quality assurance, and radiation protection [41]. Notwithstanding, Medical Physicists have been at the forefront of the application of AI technology to medicine, including the creation and improvement of imaging technologies as well as many other innovations that have boosted the quality of radiotherapy service delivery [87]. As an example, the knowledge-based treatment planning system, which uses machine learning algorithms to construct high-quality, automated radiotherapy plans using patient images, contours, and clinical data, was created by medical physicists [41]. When the auto-planning systems are finished, their results must be tested before being approved in full. However, due to each patient's individual anatomy, the proposed plan is usually customized and adjusted by clinical medical physicists during this time. A clinically acceptable solution is reached when potential problems with a particular strategy led by the medical physicist are discussed with other team members, such as oncologists, therapists, and dosimetrists [41].

It is the responsibility of the Medical Physicist to carry out an appropriate routine Quality Assurance (QA) test program with clearly defined frequency, metrics, tolerance levels, and actions to be taken in case of test failure in order to guarantee that clinically used AI algorithms continue to perform with the desired level of accuracy [41]. Medical Physicists design QA tools that guarantee the finest image quality. The Medical Physicist performs QA utilizing properly prepared in-phantom film/ion chamber measurements and comparing them against previously published dose calculation procedures in order to validate the dose predicted by deep learning AI algorithms. They also help determine the cause of a machine failure and implement corrective measures, such as calibrations or quality control tests, when AI techniques forecast a LINAC machine failure [13]. As part of QA activities, medical physicists are responsible for ensuring patient safety during radiotherapy. Machine learning has the ability to lower the risk of radiation exposure to patients and the radiotherapy team without compromising image quality during imaging procedures [40]. Medical Physicists work to ensure that they establish clinical evidence for all existing and new AI applications in radiotherapy service delivery. They also make sure that all operators are trained in the usage of the best imaging techniques and ensure that radiation protection measures are in place [13].

Not only do routine QA activities show the relevance of Clinical Physicists, but also non-routine actions. Medical Physicists' non-routine activities in a typical radiotherapy department include implementing novel procedures into clinical practice, commissioning treatment equipment, and offering patient-specific consultations [88]. During the commissioning of treatment equipment (e.g., LINAC) for clinical use, Medical Physicists perform thorough measurements of dosimetric parameters required to validate the treatment planning systems in order to arrive at the best radiation modality and treatment approach for each patient. In addition, they also create operational procedures, entering of beam data into the treatment planning system, and testing of the accuracy of that system [89].

In the same way, careful commissioning into radiotherapy clinical practice is necessary for any AI technology [88]. The typical method for accomplishing this is to first interface the AI tool with the commercial treatment planning system (TPS), after which the vital patient anatomy data are supplied to a selected workstation. However, it's not as easy to commission a new radiation therapy technology as it is to assess LINAC dosimetric performance. Clinical physicists must engage and discuss the procedure with every team member within the department. When the supply of all the patient anatomy data to the workstation is completed, AI optimal fluence maps are also imported into the TPS for the purpose of leaf sequencing, dosage estimation, and possible fine-tuning. The treatment team led by the clinical medical physicist works together to evaluate and validate the workflow and performance of the technology [88,90,91]. As a result, Medical Physicists would continue to play a leading role in the optimization of radiotherapy procedures when AI technology is eventually introduced and implemented across all radiotherapy centers in Africa.

9. Conclusions

The purpose of this study was to assess the readiness of Africa for the introduction of Artificial Intelligence Technology into radiotherapy service delivery. To achieve this aim, a narrative review was conducted from relevant databases to identify challenges that might limit the introduction of AI technology into radiotherapy practice. The first challenge identified was insufficient data needed to adequately train and validate AI models. The lack of sufficient data is a result of the unavailability of national data banks in all African countries as well as resources of AI technology such as storage clouds. The second challenge was legal and ethical issues related to rights and ownership of the data. The third major issue identified was the exclusion of AI content in the educational curriculum for training radiotherapy personnel/students. To make sure students are aware of the clinical applications, potential advantages, and related hazards, fundamental and advanced courses in AI machine and deep learning techniques must be introduced at both the undergraduate and postgraduate levels, respectively. The absence of AI content in the African educational curriculum is due to the limited number of AI teaching professionals. The fourth challenge has to do with funding, which requires massive investment in AI technology resources. As African countries prepare for the introduction of AI technology into radiotherapy service delivery, these challenges must be addressed unanimously. This means that the management of all national radiotherapy centers, radiotherapy training, and educational centers, governments, and relevant stakeholders must work together to provide the needed solutions toward the successful integration and implementation of AI technology into radiotherapy practice.

Author contributions

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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