The changing role of radiation oncology professionals in a world of AI – Just jobs lost – Or a solution to the under-provision of radiotherapy?

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1. Introduction

The main task of radiation oncology is planning and delivery of high precision radiotherapy to cancer patients. Since radiotherapy is relevant for more than 50% of all cancer patients, the role of radiotherapy in cancer management is substantial. Radiotherapy involves use of advanced technology, both for imaging, planning and delivery of treatment and follow-up, and requires labor intensive procedures by highly specialized health professionals. Not all countries have the required resources to offer proper access to radiotherapy. The ESTRO-HERO analyses showed that the optimal radiotherapy utilization benchmark is not met in the vast majority of countries, not even the most affluent and well-served countries. Despite improvements in equipment and staffing, there is today still a significant underutilization of radiotherapy in most European countries [1–6]. Another real challenge to European radiation oncology is the anticipated significant increase in new cancer cases over the next years, meaning that from 2016 to 2025 a 16% increase in the number of radiotherapy treatment courses has been estimated with a variation across European countries from less than 5% to more than 30% [7,8]. Within the same timeframe, cancer management will move towards more personalized, tailored and integrated care, centered around the needs of the patient and not of the system. These simultaneous trends will together put radiation oncology under pressure, but also offers a unique case for automation and use of artificial intelligence (AI) to alleviate and optimize workflow and quality of care. In this commentary, we will briefly outline the AI applications in radiotherapy planning, delivery and quality assurance, and give our perspective on how this will change the roles of the professions involved.

2. Overview of AI applications in radiation oncology

Artificial intelligence is a broad term covering the simulation of human intelligence or problem solving capabilities using computers/machines. In a more narrow sense, the term is often used to cover use of machine learning methods in which the computer automatically learns from data (and experience), identifying underlying patterns in complex systems, to perform predictions. Deep learning is a subcategory of machine learning mimicking how the human brain works by feeding information through multiple processing layers. There are numerous ways to utilize artificial intelligence in radiation oncology throughout the treatment chain, especially in image analysis, risk modelling, treatment planning, and quality assurance. In the following, we will go briefly through the most predominant applications of AI in RO, their place in the treatment chain, and their status of implementation. We will not go into detail regarding the relevant type of artificial intelligence, however in most cases some level of machine learning is used. While deep learning appears promising for several applications [9], it is still in an early stage of maturation. The use of artificial intelligence in different aspects of radiation oncology affects workflow in different ways, and we will discuss this in the following section.

2.1. Image reconstruction

When medical images (CT, PET, MR, SPECT etc.) are acquired, the first step is the so-called reconstruction process which involves mathematical transformation of the detected signal into visual images. The image quality can be highly dependent on the algorithm used for reconstruction, and some features are hard to resolve (such as metal artifacts in CT scans). Use of machine learning methods to assist or replace traditional reconstruction methods have been shown to reduce artifacts and potentially increase quality and consistency of reconstruction [10,11].

2.2. Image registration

Often several imaging modalities are used for segmentation of structures prior to treatment planning, in particular PET, CT and MR (various sequences). These images then need to be co-registered in order to achieve optimal quality of segmentation. In addition, several images may be required longitudinally during treatment (for instance in-room cone-beam CT images or MR images). More advanced registration of these images with the

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original planning image will require deformable image registration, which is not a trivial task [12]. For such registration tasks, deep learning methods are being developed which can perform rigid and deformable co-registration of images automatically and fast, for instance based on an unsupervised training model as investigated in [13].

2.3. Image segmentation

One of the most time-consuming tasks in pre-treatment preparation is the segmentation of structures, including organs at risk and target delineation. In addition to being time consuming, this step involves large intra- and inter-observer variations, leading to suboptimal dose distributions [14]. Automation of segmentation and delineation has been extensively investigated, especially for organs at risk, using both atlas-based and machine learning methods [15,16]. Auto-segmentation of organs at risk has been shown to reduce the workload, and potentially increase consistency in several clinical sites, while there are yet no clear results for automation of target delineation.

2.4. Image analysis

The introduction of advanced computerized image processing has opened a new potential for identification of image features not quantifiable by visual inspection. Such features relate to 2D or 3D spatial dispersion of gray scale values and can for instance include pixel intensity histograms and gray scale run lengths. The field coined radiomics encompasses investigations of quantification of such features in images (imaging biomarkers) and their correlation with treatment outcome. The analyses are based on machine learning techniques, where patterns are mapped between up to thousands of such features and various outcome measures in retrospective patient cohorts, for identification of potential predictive power of images acquired before or during treatment [17].

2.5. Risk modelling and profiling

With the vast amount of digital patient data becoming available (including images), advanced pattern finding by use of artificial intelligence may reveal correlations between clinical outcome and various risk factors and/or biomarkers. This again can serve to strengthen outcome modelling, and provide potential for new patient stratification regimes for treatment personalization [18,19]. Such new schemes need to be tested in new prospective clinical trials, and successful trials will increase the number of available treatment options including the requirement for data acquisition and analysis for the individual patient in the diagnostic and preparatory phases.

2.6. Treatment planning

Optimization of radiation dose distribution is a highly iterative process which entails a large degree of user interaction. The challenge is to balance limitation of doses to organs at risk with achieving adequate coverage of targets, which often involves making several trade-offs and compromises of various parameters, in turn making the process complex and difficult to overview – as well as time consuming - for the individual planner. Use of automating techniques for treatment planning has been introduced in the last 5+ years, showing high potential for improving both efficiency and quality of treatment plans [20,21]. The field is still in development as reviewed recently in [22]. As daily plan adaptation becomes the next step in development of high-precision radiotherapy, the speed of treatment planning becomes important for achieving a viable

workflow thus emphasizing even more the relevance of automated planning [23]. This is already a reality in newer applications including both integrated MR treatment units (MRIdian, ViewRay Inc and Unity, Elekta AB) and cone-beam CT based online adaptive systems (ETHOS, Varian Medical Systems, Inc).

2.7. Quality assurance

One of the basic rationales for physicists in radiation oncology has traditionally been to perform quality assurance of both hard- and software in the clinic, including basic dosimetry, machine performance/constancy, and patient specific dose measurements. These are tasks that are primarily carried out after-hours on a regular schedule, often with a short deadline for clinical acceptance, and involving a large amount of data analysis. Automation and data mining can be used to optimize quality assurance schedules, and to auto-detect and identify errors/deviations. Upcoming error modes or machine breakdown may potentially even be predicted based on pattern recognition in retrospective measurements [24], and machine log files can be analyzed for detection of errors during delivery, such as MLC leaf positioning [25].

3. Effects of AI on clinical practice

Based on the summaries above, we can broadly divide applications into two categories – those aimed primarily at automation and those exploring data mining. The categories are not mutually exclusive, but the categorization serves to qualify their effect on future practices and developments.

Applications primarily aimed at automation will have a direct impact on workflow in the clinic, and on the tasks performed by professionals. A good example of this is use of auto-segmentation tools for organs at risk in CT scans (or other imaging modalities). This was previously a tedious and time-consuming manual task performed by various professionals depending on local standards and difficulty (clinicians, physicists or radiographers). Automatic tools are now available to a large extent, reducing the time spent by humans on the delineation step of the treatment preparation process. As more and more organs at risk are being considered in treatment planning (due to increasing quality of imaging and precision of treatment), this automation contributes to avoid an otherwise increasing bottleneck in the workflow, releasing valuable time for other tasks requiring human interaction. These tasks may include those not yet automated, those not automatable, and not least new tasks arising from the wealth of opportunities provided by data mining (see below). The category of automation applications include image reconstruction, registration and segmentation, treatment planning, and QA error identification. In addition to assisting in workflow, automation of these processes can improve consistency and quality of difficult tasks, such as image registration, and thereby reduce uncertainties in the treatment chain.

Data mining applications, on the other hand, aim to provide new insights based on pattern recognition in large databases. This may not immediately affect workflow in the clinic but may produce development of new treatment options brought into clinical protocols and trials. An example of this is radiomics studies mapping correlation of advanced image features in scans with outcome measures after radiotherapy. The results of these studies may indicate new treatment options – such as new patient stratification or altered fractionation schedules – to be tested in clinical trials and eventually implemented in new clinical protocols. The research and developmental work involved in such data mining studies require participation of professionals at all levels. Due to the increasing availability of digital data – images, electronic patient

journals and digital registers - the opportunity and relevance of data mining studies is increasing, and the workload involved in such studies is in turn also increasing. This involves new tasks not traditionally part of radiotherapy treatment chain, in particular in relation to data science.

4. Will AI replace professionals in radiation oncology?

There is no simple answer to the question how AI will affect professionals in radiation oncology. However, it is clear that automation will replace many manual tasks performed today. Examples are many: delineation of organs at risk and even target volumes, manual treatment planning, verification of treatment position and delivery of treatment. These are all procedures that, when replaced by AI, will increase efficiency and reduce the time spent on planning and treatment. The arrival of new commercial software products [26] already indicate that automation of work-flow is something we will face in the very near future.

On the other hand, automation of workflow will not just remove tasks but also create new opportunities [27] – for all professionals in radiotherapy, medical doctors, medical physicists, radiation therapists, radiographers. Hence the role of the professionals will drift from a weight on performance of manual tasks to more weight on development, individualization and evaluation of radiation treatment.

For the radiation oncologist (and partly the radiologist) organ at risk (OAR) delineation has already partly been taken over by radiation therapists, if not being segmented using algorithms [28]. Very likely the future will also bring automated segmentation of target volumes. Radiation oncology will for the medical doctor change from a technical to a much more clinical and holistic specialty allowing to focus more on the patient and the entire clinical care. Radiation oncologists must therefore position themselves as responsible medical doctors, being involved in the entire care path, including handling of side effects, palliative care and clinical and translational research. Radiation oncology professionals must redefine their professional role and become actively integrated in patient-centered, multidisciplinary health care. Otherwise, the medical specialty will become 'task-shifted' and superfluous.

For the medical physicist and RTTs treatment planning is a large parts of the clinical work. Treatment planning will soon face a shift in task-roles as automated planning becomes superior and less time consuming compared to manual planning [20]. The potentials are enormous, and successful implementation of AI will be necessary for wide-spread implementation of "plan-of-the-day" evaluations for most patients as well as for more precise treatment (like protons and MR-Linear accelerators). It is very likely that development of more specialized and patient individualized treatments will be the focus for medical physicists whereas more simple plans like volumetric arc therapy (VMAT) will be fully automated.

Quality assurance, which makes up a basic part of the medical physicists role will also be affected by automation possibilities as described above, however the procedure of actually performing the physical dosimetric measurements will inevitably remain a manual task to some extent.

Likewise, classical radiation therapist roles like OAR delineation, treatment positioning and verification will be replaced by AI and tasks will shift to e.g. treatment planning. Already now some institutions subspecialize radiation therapists to perform specific treatment plans like palliation or breast irradiation. Although not yet proven to be more efficient and of higher quality.

These changes in work procedures will not just benefit high income countries but also countries with less developed infrastructure and lack of specialized staff. AI is a very attractive way to close the gap in the need for radiotherapy across the world [29,30].

One of the immediate challenges that we face is to educate the health care professionals in aspects of safe implementation of AI tools, defining QA, commissioning standards for AI tools, and how to use AI technologies prudently. These are tasks that cannot be left to the industry. Scientific organizations like ESTRO and ASTRO have a huge responsibility to secure a scientifically sound dissemination of knowledge in the field. ESTRO and the ESTRO School have taken these initiatives and educational offers will be available as scientific meetings, courses and workshops in the years to come.

In conclusion, the increasing future demands for individualized high tech radiotherapy to a growing number of cancer patients will require that the radiation oncology profession must utilize automation and AI to secure that our professional resources and roles can be aligned with the needs of the emerging patient-centered, multidisciplinary health care.

Declaration of Competing Interest

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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