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Artificial intelligence technology for radiation oncology understaff mitigation and cost-effective treatment planning

Inteligência artificial para planejamento de tratamento e auxílio na escassez de profissionais em radioterapia

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ABSTRACT

Treatment with radiation therapy can be relatively inexpensive and highly effective, reducing the overall cost of healthcare, as well as saving lives of cancer patients. To face the posed challenges of laborious tasks and understaff in radiotherapy, the use of knowledge-based models (artificial Intelligence) to reduce the treatment planning times up to 95% might be a promising solution. One such tool, called RapidPlan (Varian Medical Systems, Palo Alto-CA), could be acquired with an investment of a small fraction of the treatment planning system cost. RapidPlan's support during treatment planning results in a considerable increase in plan quality while reducing plan variability and elaboration time. The goal of this dissertation was to estimate the break-even point from where the time saved during treatment time would pay the initial investment on RapidPlan. Published data demonstrates that RapidPlan can largely benefit radiation therapy institutions by streamlining the treatment planning process and the break-even point started to be achieved after treating 112 to 2668 patients, depending on the cancer types treated for each group. Therefore, it may be possible to realize a return on investment within a reasonable time frame, while benefiting from gains in efficiency, and possibly mitigating understaffing and lack of experience in treatment planning.
Keywords: artificial intelligence; radiotherapy planning, computer-assisted; health care costs; investments; neoplasms.

RESUMO

O tratamento com radioterapia pode ser relativamente barato e altamente eficaz, reduzindo o custo geral dos cuidados de saúde bem como salvar vidas de pacientes com câncer. Para enfrentar os desafios impostos por tarefas laboriosas e falta de mão-de-obra na radioterapia, o uso de modelos baseados em inteligência artificial para reduzir os tempos de planejamento de tratamento em até 95% pode ser uma estratégia promissora. Um exemplo de tal ferramenta, denominada RapidPlan (Varian Medical Systems, Palo Alto-CA) pode ser adquirida com o investimento de uma fração do custo do sistema de planejamento de tratamento. O suporte do RapidPlan durante o planejamento do tratamento pode resultar em um aumento considerável na qualidade do plano, reduzindo a variabilidade e o tempo de planejamento. O objetivo desta dissertação foi estimar o ponto de equilíbrio a partir do qual o tempo economizado durante o tempo de tratamento pagaria o investimento inicial no RapidPlan. Pela avaliação dos dados publicados, pode-se concluir que o RapidPlan pode beneficiar amplamente as instituições de radioterapia, agilizando o processo de planejamento do tratamento e o ponto de equilíbrio começou a ser alcançado após o tratamento de 112 a 2.688 pacientes, dependendo dos tipos de câncer tratados para cada grupo. Portanto, é possível prever um retorno do investimento em um tempo razoável ao mesmo tempo que se usufrui de ganhos em eficiência e potencial mitigação da falta de pessoal e experiência em planejamento de tratamento.
Palavras-chave: inteligência artificial; radioterapia; planejamento da radioterapia assistida por computador; custos de cuidados em saúde; investimentos em saúde; neoplasias.

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INTRODUCTION

In the digital age, radiation oncology has shown important advances due to advancements in image-guided precision radiation therapy, cloud-based information technology, remote treatment planning, quality assurance, training, data collection and artificial intelligence [AI] tools. As a result of these developments, and due to the greater emphasis on early cancer detection and the consequent need for curative therapy, radiation therapy [RT] has a sustainable impact on future cancer care, emphasizing its cost effectiveness and long-lasting benefits.[1]

There is a necessity of a collective transformation to expand access to high-quality radiation therapy and deal with the COVID-19 induced cancer backlog and the future cancer burden worldwide.[2] The emergency situation due to COVID-19 brought focus to curative cancer treatment, so radiation therapy was prioritized over other cancer therapies.[3] It led to radiation therapy centers exchanging experiences more frequently, and radiation therapy was identified as a safe COVID-19 cancer therapy that could be used to continue treating patients during the pandemic, as well as even a substitute for cancelled surgery for some malignancies.

Treatment with radiation therapy can be relatively inexpensive and highly effective, reducing the overall cost of healthcare, as well as saving lives.[4] It has been shown that full access to radiation therapy might require large investments, but the investment begins to pay off after 10 years when rolled out over 20 years and compared to human capital benefits over those years.[5] There is insufficient access to radiation therapy around the world and a lack of funding devoted to it. Radiation therapy is used in more than half of cancer patients and is involved in 40% of cancer cures.[1] Despite of its high efficacy, only 7% of the cancer care budget in Europe is spent on radiation therapy.[4]

AI has been investigated for different applications in medicine, including radiation therapy. AI methods aim to reproduce complex tasks in a timely manner with sufficient quality. AI has also been applied to improve the outcomes of time-sensitive cases[6,7] and to free up time for pressing patient-related needs.[8] For example, AI has been applied to auto-contour organs at risk[9] and to help prioritize patients at risk of developing colorectal cancer.[10]

Radiation oncology treatments involve a detailed planning process, where a trained professional, such as a dosimetrist, may spend several hours optimizing the radiotherapy plan.[11] RT departments might also be challenged due to lack of staff, caused by financial or qualification issues.[12] Therefore, manual treatment planning can be a time-consuming, thus an expensive activity which might reflect in overall treatment costs and decrease the treatment capacity of a radiation therapy service.

Patients from low- or middle-income countries might need to face long waiting times due to a shortage of capacity, which might directly impact the outcomes. As in Brazil, where among lung cancer patients, a study[13] found that treatment is usually provided within a reasonable period of time, in accordance with the 60-day law; there is, however, an association between individual characteristics and the time to treatment, service provision in macro regions and factors related to it. Oncology service distribution reflects differences reported. Some regions may be underserved, while others may be overburdened thus treatment time is significantly impacted by these factors. As a result, health care provision differs based on the patient's place of residence. Reports of disparities are possibly due to health access differences to care services. Data derived from cervical cancer patients[14] allowed to conclude that the wait of up to 60 days increased the risk of death, reinforcing the idea of that, when diagnosed with cancer, treatment should be started as soon as possible, preferably before 60 days. A large number of cancer patients who require radiation therapy in the Brazilian public health system do not have access to this treatment. The lack of RT treatment has a considerable negative impact on cancer survival; if radiation therapy was universally available, over 5000 deaths in the most prevalent cancer types would likely be avoided.[15] Universal access to radiation therapy is a very cost-effective public health project[16] that should be prioritized.

In determining the ensuing costs of radiation treatments, the applied fractionation modes, including dose distribution and the amount of time necessary to execute certain tasks, appear to be the most relevant. It's also crucial to consider the number of individuals who have been irradiated, which varies depending on the type of therapy modality utilized. Treatment planning and delivery tasks use the most effort and account for a significant percentage of total time. Advances in radiotherapeutic methods have enabled improved irregular target volume irradiation, as well as the potential of dose escalation, resulting in demonstrated improvements in treatment outcomes. When compared to 3D-CRT, the clinical efficiency of IMRT is notices, as it provides better quality of life more efficiently. For prostate cancer, the difference equated to approximately 20 additional QALYs for every 1000 treated patients, while IMRT offered significant advantages in terms of treatment efficiency, reduced toxicity, and lowered long-term care costs.[17,18] To face the posed challenges of laborious tasks and understaffing in radiotherapy, the use of knowledge-based models (artificial Intelligence) to reduce the treatment planning [TP] times up to 95% (19) might be a promising solution. One example of such tool, called RapidPlan (Varian Medical Systems, Palo Alto-CA), could be acquired with an investment of a fraction of the treatment planning system [TPS] cost. RapidPlan's support during treatment planning might result in a considerable increase in plan quality and a reduction in plan variability. RapidPlan has been shown to be a useful tool for supplementing the planning capabilities of less experienced planners, resulting in greater treatment plan quality uniformity.[20] As a result, a faster and efficient AI-assisted workflow would allow a return of the investment in forms of increased treatment planning capacity and freeing dosimetrists time for other activities. This could partially address Brazilian long waiting times for treatment, as mentioned above, especially for patients that rely on the public health system.

The goal of this dissertation was to estimate the break-even point from where the time saved by using RapidPlan's AI-assisted workflow would pay its initial investment.

MATERIALS AND METHODS

By reviewing published studies, costs and time estimates for RT-related activities could be obtained. The focus hereafter will be on dosimetrist wages and time spent on treatment planning. Published studies regarding the use of AI for automatic planning will be the source of time comparisons between manual and automated workflows.

As an important additional module to the TPS, the authors find reasonable to estimate RapidPlan's cost being around 20% of the total TPS price for return on investment [ROI] calculation purposes, due to the lack of published costs associated with this software license. A previous study estimated the value of a treatment planning system from vendor quotations in 2014.[21] In this study, the cumulative inflation of 12.37% (2014-mid 2022) was considered for the calculations.

Considering the dosimetrist is the main responsible for treatment planning, the mean hourly wage used in this study is approximated to $30, after inflation correction based on published data.[21]

The number of patients and cancer types treated can vary immensely between institutions. Therefore, estimations were calculated based on published results from different institutions and are intended to be used as an example on how much time can be saved by using RapidPlan. Based on the peer-reviewed data for treatments of different anatomical sites, economic estimations were calculated to provide the amount that could be saved in US dollars when using RapidPlan, which would later result in a break-even point after a certain number of patients was reached for each case. The method applied to estimate the break-even point is demonstrated in eq.[1]

$$Break-even \quad = \frac{RapidPlan\ license\ cost}{Cost\ savings\ per\ patient} \quad (1)$$

Where Break-even is the number of patients planned when the amount of monetary resources saved would equal the initial investment on the RapidPlan software license; RapidPlan license cost is the value estimated to license the product for clinical use; Cost savings per patient is the amount of monetary resources saved due to the automation of the treatment planning per each patient under determined conditions.

By having the same intent of delivering a homogeneous prescribed dose while preserving the organs-at-risk [OAR], using the same TPS and RapidPlan, treatment planning times are expected to be within a comparable range for similar clinical setups across institutions. Therefore, based on published results, estimations of the break-even would serve as an indication on how much time could be spared during treatment planning, which potentially can be translated into freeing resources or mitigating an understaffed department. Results from each institution were not directly compared but rather presented as complementary information, since the time required for treatment could drastically change accordingly to the treated area, patient-specific challenges or even a combination of these two or more factors.

In principle, users can use a model created by another institution, re-train it or create a new one based on own database. It is worth mentioning that the costs associated with training a RapidPlan model is not considered due to insufficient published data.

RESULTS

RapidPlan has been proven successful on this task of speeding up the treatment planning process while reaching clinically acceptable treatment plans, as will be shown from peer-reviewed studies results in the following text.

At VU University Medical Center (Amsterdam, The Netherlands), a study was published for automated treatment planning for breast plus locoregional lymph nodes.[11] For the manual and automated plans, respectively, the average overall planning time frames were 163 ±97 and 33 ±5 minutes, with 130 and 5 minutes of planner interaction. The authors created an automated system for individualized treatment planning of breast plus locoregional lymph nodes employing a hybrid RapidArc approach, utilizing the TPS programming API and RapidPlan. The quality of the resulting plans was typically on par with or better than the corresponding manual plans, which saw noteworthy reductions in treatment planning times. Such level of automation might ease the institutions workload and promote the adoption of novel therapeutic approaches. And it is especially relevant, considering that breast cancer is the most frequent cancer type in women.[22] Under the wages values assumed for treatment planning described on the previous section ($30/hour), the average time saved for the 15 patients would roughly result in a total of 1950 minutes (130 min/patient), therefore a $ 975 difference. Such a difference would require 920 patients to the break-even point of the estimated RapidPlan license cost.

Published results from Hong Kong demonstrates that for complex cases as of nasopharyngeal cancer patients [NCP], the use of RapidPlan significantly (P<001) reduced the planning time from 295 to 64 minutes.[23] Nine out of the 20 patients could have clinically acceptable treatment plans by using RapidPlan alone, and in total for 19 patients it could achieved such quality level plans with manual touch-up afterwards. Minor manual touch-up was sufficient for those RP plans that could not initially meet the plan acceptance requirements and essentially yielded the same quality as those that did not require any further operator interaction. When compared to the overall planning time for the manual plans, the increase in planning time with manual touch-up was rather insignificant. Furthermore, the new patient data used in these evaluations could be applied to further train the model, thus improving its future performance. In conclusion, for this study, the time saved for the 20 patients was 4,620 minutes (231 min/patient), which we could estimate as a $ 2,310 economy and in such a rate the break-even would be reached with 520 patients.

In addition, automated planning has been used for challenging cases of hippocampal-sparing whole brain irradiation [HS-WBRT] in a study conducted in Chicago.[24] For HS-WBRT, planning and delivery were totally automated thanks to HyperArc [HA][25] technology and a RP model. Together, the automatically created plans and automated therapy delivery boosted the consistency and effectiveness of planning, by providing the possibility of delivering a complex high-quality therapy in a safe and quick manner, thus ultimately enhancing patient care. For such cases RP made possible to reduce the treatment planning times from 540 minutes to 40 minutes or less. For the 10 patients included in the study, the time reduction amounted to more than 5,000 minutes, which we assume as a cost of $ 2500 for planning efforts. For this type of treatment, the break-even point would be at 240 patients.

Prostate cancer is the most frequent cancer type for male patients.[22] A study from Japan, performed a dosimetric comparison of manually and automated treatment plan for volumetric modulated arc therapy [VMAT] for prostate cancer patients.[26] For patients with prostate cancer, the RP plans produced by a single optimization were clinically acceptable. Regardless of the planner's expertise and experience, they were able to demonstrate a reduction in optimization time. For the 30 treatment plan comparisons, the time saved was at least 45 minutes. Which means more than 1350 minutes; therefore, we could estimate as a $ 675 economy and a break-even point of around 2668 patients. Where the time required to achieve such number of patients might vary drastically depending on the capacity of the clinic.

Given its high incidence,[22] lung cancer might also benefit from faster and efficient treatment planning process. As an example, due to the relatively large size of the target and the necessity to protect vital organs that overlap or are located within the target volume, treatment planning for malignant pleural mesothelioma is a challenging task.

An institution from New York published results showing that with less time spent on treatment planning and a higher prescription dosage, the RapidPlan model for malignant pleural mesothelioma demonstrated greater organ sparing.[28] The authors of this study concluded that KBP with RapidPlan may be utilized to create models for a challenging cancer type as mesothelioma. Furthermore, critical organs were better protected by the model developed in this study than by manual treatment planning. The quality of such RapidPlan treatment plans were at least on par with or better than the corresponding manual plans. Additionally, standardized clinical plans may be created faster by using RapidPlan than manually created ones, and the quality of the model may be further enhanced by further adding patients and re-training it. The average planning time for the study with 23 patients was less than 21 minutes with RapidPlan against over 4 hours with manual planning. This would result in, at least, 5,037 minutes less and an estimated economy of $ 2,518.5 in labor time. The break-even point, at such rate, would be reached at 548 patients.

A comprehensive study from an Australian institution describes their experience after implementing RapidPlan for 7 months and creating plans for 496 patients for a variety of anatomical regions.[19] They concluded that plans optimized using RapidPlan show clinically acceptable quality while greatly increasing the workflow efficiency. RapidPlan not only produced plans of at least equivalent quality to those created manually, but also shortened planning time by more than 80% in the majority of subsites. More uniform treatment planning both inside and between institutions can be accomplished by this tool effectiveness. In addition, the quality of treatment plans may continue to be refined and departmental efficiency may increase as models are revised and improved over time. The average time for each anatomical site was taken from this study and included in Table 1, where the percentage variation of the time taken for planning manually and with Rapid plan was calculated for each anatomical site. Table 2 represents the financial impact these time differences would have under our defined planner earnings.

Table 1. Average times for manual and automated planning for each anatomical site.

Model name	Average time manual planning (min)	Average time RapidPlan planning (min)	Percentage decrease in planning time
CNS	178	38	78.7%
LungSBRT	185.3	38.3	79.3%
Oesophagus	100	40	60.0%
LiverSBRT	622	28.75	95.4%
Rectum	1137.5	53.89	95.3%
Anus	720	40	94.4%
Gynae	805	50	93.8%
Bladder	300	42.5	85.8%
Prostate	390.7	44	88.7%
Prostate + LN	456.7	91	80.1%
Average	489.5	46.6	90.5%

Source: [19]

Table 2. Financial impact of the average time taken for manual and automated plan for each anatomical region.

Model name	Manual planning cost $	RapidPlan cost $	Cost difference $
CNS	89.00	19.00	70.00
LungSBRT	92.65	19.15	73.50
Oesophagus	50.00	20.00	30.00
LiverSBRT	311.00	14.38	296.63
Rectum	568.75	26.95	541.81
Anus	360.00	20.00	340.00
Gynae	402.50	25.00	377.50
Bladder	150.00	21.25	128.75
Prostate	195.35	22.00	173.35
Prostate + LN	228.35	45.50	182.85
Average cost	$ 244.76	$ 23.32	$ 221.44

Source: Author's calculation based on time estimations from Table 1.

Considering this particular mix of patients, the break-even would require only 272 patients. Which could be achieved in a relatively short time frame, especially considering that the number of patients included in this study was 496.

DISCUSSION

During treatment planning, the optimization inside the TPS uses mathematical descriptions of clinical goals to determine the most efficient dose-volume distribution, respecting published statistics about controlling the disease or complications due to the treatment. This process is often time-consuming and extremely operator-skill-dependent, given that iterations are required when there are trade-offs between conflicting objectives, such as treating the lesion and sparing a sensitive organ. A major difficult task for the operator is converting clinical goals into practical optimization goals. For example, to treat locally advanced head and neck cancer can impose many hurdles, specially defining the dose constraints to important structures that are either overlapping or adjacent to the target volumes.[29] Altogether leading to substantial variability in the plan's quality.[20]

Many opportunities have been explored aiming to streamline the treatment planning task while attaining high quality on such plans, such as planning automation (30,31), knowledge-based planning [KBP][32,33] or multicriteria optimization.[34,35] The KBP technique, the same as used by RapidPlan, entails developing high-quality treatment plans by leveraging DVH prediction models that were generated from statistical examination of groups of clinical data from previous patients. To that end, during the treatment planning process, the operator can easily use this trained model to forecast the ideal dose distribution for every new unique patient anatomy.

Due to few resources and understaffed hospitals, cervical cancer has a high incidence and fatality rate in low - and middle-income nations.[36] By expediting the radiation treatment planning process, RapidPlan might also alleviate understaffing problems. Similar to previously cited studies, one optimization derived from RapidPlan is already likely to produce acceptable clinical treatment plan while reducing the waiting time to start the treatment for such type of cancer.[37] To properly evaluate the efficacy of RapidPlan as a tool for multicenter clinical study design and quality assessment, RapidPlan validation should be undertaken in a planned clinical trial dataset for which a meaningful planning comparison can be done.[19]

By evaluation of the published data, it could be concluded that RapidPlan can largely benefit radiation therapy institutions by streamlining the treatment planning process. In some cases, it made possible a time reduction of over 90%, which become even more impactful when dealing with challenging cases like HS-WBRT planning, where the manual treatment planning takes around 9 hours to be completed. Even when the time saved in minutes is smaller, for cases like prostate and breast cancer, due to the high incidence of such malignancies, the time and efforts saved by using RapidPlan would rapidly add up to a considerable amount. Therefore, it is reasonable to foresee a return of investment in a relatively short time, while benefiting from gains in efficiency, and possibly mitigating understaffing and lack of experience in treatment planning.

It is important to acknowledge that the applied methodology for calculating break-even points is based on certain assumptions, such as uniform distribution among treatment sites. This may not accurately reflect real-world scenarios where disease prevalence can vary significantly. Furthermore, our study focused on a specific patient population and may not be generalizable to other populations. As such, the break-even points presented in this paper should be interpreted with caution and may not be applicable to all institutions and patient populations. It is important to gather additional data and tailor the methodology to the specific patient populations and resource limitations of individual institutions to accurately determine break-even points.

An alternative approach to estimate the break-even results would be to calculate it as the ratio of patients treated to license cost. This would allow readers to use our findings to indirectly estimate the cost of a license based on their patient volume and expected break-even point. Additionally, it is important to estimate the number of patients that can be planned under a single license for each institution, which will give them an idea of the upper limit of how fast their break-even time would be. We recommend that readers use our results in conjunction with their own estimates to make informed decisions about RP implementation.

FINAL CONSIDERATIONS

The main goal of the present study was to present estimates of monetary resources saved due to the implementation of a time-efficient AI treatment planning tool. Faster treatment planning would result in a larger capacity to assist patients, allow earlier start of the treatment, give the possibility of using the dosimetrist expertise in another area (such as organ contouring), and mitigating the shortage of experienced staff. These results would offer an overview on the gains from the initial investment of acquiring the software. Therefore, serve as basis for decisions for private and public institutions that want to benefit from an optimized radiation therapy workflow. The conclusions expressed in this work are those of the authors. They do not intend to reflect the opinions or views of Varian, a Siemens Healthineers company, or its members.

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