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International Journal of Innovation Studies

A STATE-OF-THE-ART REVIEW OF ADAPTIVE SCHEDULING AND OPTIMIZATION IN RADIOTHERAPY: BRIDGING OPERATIONAL RESEARCH AND CLINICAL PRACTICE

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Abstract

Background: Radiotherapy (RT) scheduling is an important element in managing the schedule for treatment and reimbursement, as well as managing scarce resources to benefit as many patients as possible. Standard scheduling algorithms fail to consider dynamic factors such as time, working machine availability, each patient's unique situation, and interruptions that require powerful algorithms. **Objective:** The study aims to discuss the existing techniques that help optimize RT scheduling, emphasizing adaptation and Artificial Intelligence (AI) to reduce operational constraints, enhance the flexibility of the scheduling approach, and incorporate real-time decision-making. **Methodology:** Many deterministic, stochastic, and AI-based scheduling methods have been reviewed for suitability in the RT workflow. The paper discusses hybrid optimization methods, simulation-based scheduling, federated learning for distributed optimization, and policies for advocating scheduling solutions. **Results:** There is evidence that enhancing the integration of AI and Machine Learning and using real-time optimization in the work schedule improves scheduling efficiency. Enhancing the deterministic models with AI increases efficiency, whereas real-time scheduling, such as rolling-horizon and multi-agent systems, contributes to dynamic decision-making. However, challenges like computational difficulty, issues relating to compatibility, and clinician unwillingness act as barriers. **Conclusion:** Bringing research into clinical practice calls for collaboration and interaction between different professionals, common practice protocols, and exponentially growing AI-based schedule solutions. Future work should also aim to develop real-time adjustments and address the ethical practice of integrating AI into clinical work to enhance RT scheduling.

Keywords: Radiotherapy (RT), Optimization, Adaptive Scheduling

1. Introduction

Radiotherapy (RT) is one of the particular cancer treatment principles used in treating over 50% of cancer patients (Glide-Hurst et al., 2021). The growing number of cancer cases worldwide creates enormous pressure on healthcare facilities to properly schedule RT, thus leading to extended treatment durations and increased patient delays (Yoganathan et al., 2025). Radiation therapy relies on the accurate delivery of radiation doses to significantly help control tumor growth without harming the healthy tissues. Scheduling treatment and related services is a critical aspect in managing the delivery of care, patients' outcomes, and the overall use of resources in a healthcare setting. RT scheduling is either manual or based on predefined standards, and neither accurately reflects contemporary RT processes. Scheduling issues can result in delays in the treatment delivery and service organization, lack of or ineffective use of time, and inability to meet the changing needs of the patients (Pham et al., 2021). Therefore, there is a need for refining scheduling mechanisms that combine real-time optimization especially applying artificial intelligence (AI), to promote the best patient outcomes as well as the most efficient use of resources.

Barriers to efficient RT scheduling can be attributed to the lack of availability of treatment machines, the variation in scheduling needs of patients with different conditions, and others such as emergency patients and machine maintenance. These issues result in treatment delay, resource wastage, and inability to deliver timely healthcare (Pham et al., 2013). Adaptive Radiotherapy (ART) is a specialized form of RT that introduces additional complexities in scheduling due to its requirement for real-time treatment modifications. This means it is possible to adapt the treatment plan during the treatment period depending on anatomical and biological changes in the patient's body, making ART an individual treatment approach to RT (Sonke et al., 2019). ART integrated into primary care practice may necessitate real-time schedules with flexibility to allow modifications throughout the day (Zhong et al., 2016). Such deficiencies are likely to result in delays, lack of alignment of treatment, and lack of accurate dosing of patients, which may lead to increased radiation toxicity and disease progression (Li, Koole and Xie, 2020).

To address the challenges in RT scheduling, operational research plays a continuous and systematic role in organizational decision-making through mathematical and optimization techniques that enhance resource management and organizational flow. They enable the creation of intelligent scheduling models to schedule time for machinery to be used, prioritize patients according to their status (treatment priority based on condition severity) and avoid interruptions (machine failure or emergencies) in treatment (Dona Lemus et al., 2024). Recent developments in scheduling methods have focused on integer programming, constraint programming and heuristic algorithms that should enhance the efficiency of RT scheduling (Pham, Rousseau and De Causmaecker, 2022). However, as scheduling becomes more complicated due to unpredictable patients' needs and various treatment procedures, the use of AI and ML seems to be very prospective. To solve this challenge, AI and ML can be used to create an adaptive planning model that changes based on time, patient conditions, machine utilization, and treatment phase (Vieira et al., 2020). They hold the potential to improve the scheduling even more by signaling in real-time, by decreasing waiting times, by increasing resource usage, and by making treatment plans personalized. These technologies can enhance the possibility of reaching more RT centers, adding valuable time to treatment, and individualizing the patient's treatment program.

However, there is still a prominent issue with adapting schedules in real-time, primarily with the dynamic approach towards the RT. The current scheduling models derived by prior studies are insufficient in handling RT's dynamic treatment requirements making the clinical processes less efficient. ART is a more individualized program than standard RT that invoked real-time modifications based on certain factors related to the patient, which makes this problem even more intricate. Moreover, effective and efficient scheduling needs the coordination of oncologists, data scientists, and healthcare management professionals to design realistic and achievable solutions that integrate clinical models with optimization algorithms (Alshamrani et al., 2024).

Scheduling RT treatments is a difficult task because of the unpredictability of patient conditions as well as the RT needs. The RT scheduling performed by traditional RT models does not consider change over time at the patient's anatomy and tumor, thus, resulting in wastage of time, resources as well as suboptimal deliveries of services. These issues are compounded by the adoption of ART, which implies changing the treatment plan frequently in response to the patient anatomy and tumor motion. Although using ART has become the standard in clinical practice, the existing scheduling systems are still far from addressing the issue of dynamic adaptations that are involved in ART. This gap in adaptive scheduling methods is a significant challenge when it comes to arranging the treatment processes, necessary resources and the general patient care plan. Hence, this review seeks to assess the current available RT scheduling solutions and examine how operational research and AI can be used to address limitations of existing models. More specifically, the intended topics include the adaptation of scheduling frameworks in the context of the ART category of technologies to improve scheduling effectiveness, minimize lead times, and advance patient care.

2. Overview of Radiotherapy Scheduling

2.1. Radiotherapy Workflow and Scheduling Complexity

The RT workflow includes systems like consult, imaging, planning, QA, and delivery, aiming to implement efficient time management to reduce time wastage and enhance the quality of the treatment and the patient care, with a focus on the patient's need, goal, and preference (Sonke et al., 2019). However, RT's availability must be personalized to meet patient needs, and the availability of machines, emergencies, and maintenance makes the schedules competitively biased (Xie et al., 2023). Static scheduling methods like pre-planned schedules are not suited for ART since one may be required to make real-time adjustments based on patient specific conditions (Legrain et al., 2015). To overcome these challenges, different approaches like integer programming, heuristic, and constraint-based mostly scheduling and optimization methods were incorporated to tackle such problems and minimize the time delays (Badri, Watanabe and Leder, 2015). Also, AI and machine learning are being incorporated into scheduling plans to allow instant changes concerning clinical urgency and resources (Narasimham, 2024). Even with these developments, real-time scheduling in ART is still a challenge given the changes that are bound to occur, hence the need to enhance AI-based, data-driven scheduling (Ten Eikelder et al., 2022).

2.2. Key Constraints in Radiotherapy Scheduling

RT scheduling involves several resource constraints that determine the effectiveness of treatment and patient care. Concerning the planning temporal aspect, patient-specific factors such as tumour growth, response to the treatment, or associated diseases require personalized treatments with adjustable frequentation rates (Sonke et al., 2019). Such factors require constant supervision and changes to make timely and effective treatment while keeping the toxicities of radiation under check. There are constraints within resources such as linear accelerators, professional clinicians, and restricted treatment session slots that eventually result in bottleneck development in RT facilities (Frimodig et al., 2023). Planned treatments regularly get turned by machine maintenance, emergencies, and overbooking, calling for enhancing techniques to ensure both efficiency and quality of service (Braune, Gutjahr and Vogl, 2022). There is a large stochastic nature due to patients' conditions, unexpected delays at any stage of the treatment process and unpredicted changes in the functioning of a hospital that can be dealt with using more flexible models such as AI-driven adaptive scheduling and optimization techniques for planning and organizing work (Pham et al., 2021). These deficiencies cannot be met using traditional static scheduling methodologies because they are rigid in response to the real-time changes. , which require AI and ML to develop dynamic therapeutic schedules to accommodate the changes in constraints (Pizarro and Hernández, 2017). Integer programming and heuristic algorithms have been used to analyze scheduling issues and enhance operating outcomes (Frimodig et al., 2023). However, incorporating real-time decision-making into clinical practice is still an issue, requiring additional technical solutions known as scheduling frameworks for disease management that would address the need for patient-centred care and efficient use of (Alshamrani et al., 2024). These issues should be solved with the help of the collaboration of oncologists, data scientists, and healthcare managers to optimize RT scheduling and eliminate the time gaps while preserving the quality of services for patients (Marcela et al., 2025).

2.3. Current Approaches in Radiotherapy Scheduling

RT scheduling method requires the clinician to manually assign the slots of treatment based on the severity of the patient's case and the availability of the machines. It is often inefficient due to variability likely to occur in the decision-making process (Vieira et al., 2021). To eliminate the concern with random visits from the patient's side, rule-based scheduling focuses more on structured protocols that utilize clinical, pathological, and treatment-based criteria to assign patients to the time slots available, which may improve the scheduling effectiveness. At the same time, lessening the everyday discretionary of treatment visits by employing protocol procedures that are clinical, pathological and treatment-based (Ferini et al., 2021). However, rule-based and traditional scheduling systems, though very efficient when dealing with structures and systems are rather rigid in responding to dynamic events like machine maintenance or any emergency cases (Regiaud et al., 2021). Heuristic scheduling addresses these drawbacks by employing optimization techniques that factor in many parameters, including the machine's workload capability and clinicians' availability, to produce the most effective real-time schedule (Åström et al., 2022). Genetic programming (GP) and simulated annealing (SA) are methods which are employed to improving the RT scheduling while taking into account the patient's needs as well as organizational requirements. GP develops the treatment schedules through steps involving selection and mutations and serves the most severe patients under the available resources. SA continuously amends schedules as needed, to increase the utilization of machines, reduce wait time and provide reasonable clinician hours. Both real-time would allow the modifications of the allocated resources, thus increasing utilization efficiency due to factors like equipment breakdown or emergency situations (Piperdi et al., 2021). However, the issues are still present, and reinforcement learning to implement adaptability for real-time scheduling adjustments still needs further development (Ten Eikelder et al., 2022). Further improvements to the heuristic model could be useful in combination with the AI application in order to improve the scheduling aspect, minimize required treatment delays, and maintain high-quality patient care (Jeyakumar et al., 2024).

3. Optimization Techniques in Healthcare Scheduling

3.1. Introduction to Optimization in Healthcare

Optimization is significant in healthcare scheduling as it enhances its effectiveness, minimizes the time that patients have to spend in health facilities, and makes better use of the available resources. In radiotherapy (RT), this optimization is paramount since the delivery of treatment requires synchronization of the machine, clinicians, and patients. Pre-scheduled or rule-based planning and scheduling do not take into consideration the ever-changing scenarios in the treatment of cancer patients. In response to this, other advanced methods have been developed, thus improving the customization of the treatment plans and usage of resources. In particular, these techniques, known as MILP and CP, have been used in case management of breast, prostate and lung cancer. Research has shown that applied optimization methods help to enhance scheduling and treatment even in regard to patients with special needs regarding scheduling and other issues like unpredictable emergencies and changes in patient's condition (Galluzzi et al., 2023). These methods incorporate patient characteristics including tumor type, stage, sufficient clinical variables and other characteristics making better utilization of treatment machines, clinicians and other assets.

Over time, other methods like genetic algorithms, and simulated annealing have been adopted as techniques for optimizing RT scheduling. These techniques address variations in patients' attendance rates, the accessibility of the machines, and other incongruities (Niraula et al., 2023). Furthermore, there is even a great potential for using AI and ML to improve RT scheduling. Another AI-based approach includes reinforcement learning which has the ability of real-time schedules or treatment plans and adapt to the changing conditions of cancer patients. This is well used in handling cancer clients due to the dynamic nature of their health, caused by tumor growth, side effects of treatment, or changes in overall health. Research has indicated positive outcomes of the use of AI and ML in the creation of RT schedules especially for patients with cancer diseases such as breast and lung cancer, the schedules were realigned with the progress of the disease and clinical symptoms (Wang et al., 2023). These technologies help in increasing the flexibility of the schedule besides making efficient use of the available resources and hence the waiting time is minimized while the patients are offered more unique plans for their treatment. However, despite this potential, the implementation of AI and ML technologies in clinical practice has had certain barriers such as data handling, regulation, and integrating the systems into existing healthcare systems. Further research is required to develop such AI approaches for the enhancement of variety, appropriateness, and speed of RT scheduling with reference to the overall management of cancer patients (Alshamrani, 2024 #32; Sonke, 2019 #29).

3.2. Deterministic Optimization Approaches

Deterministic optimization is essential for healthcare scheduling since such systems' modelling provides a mathematical optimization plan to enhance the allocation of available resources and increase the operation's effectiveness. Linear programming is used extensively to solve operation problems that entail a single objective that can be optimized, such as the time a patient spends in the ward or the use of machines in a hospital, subject to linear constraints (Huang et al., 2024). However, its applicability is restricted in the operational environment and is tied to intricate scheduling decision-making, in which discrete decisions must be addressed. Mixed-integer linear Programming (MILP) is often used to overcome these disadvantages. MILP used both the continuous and integer aspects of variables, representing more complex constraints, such as the priority of the patients, availability of the machines, and the time taken in the treatment sessions (Emsamrit and Boonmee, 2024). Thus, MILP has been used to schedule the RT, involving the effective allocation of the slots and considering the limitations imposed by the resources and the individual needs of the patients (Shinde et al., 2025). For instance, in cases of treating prostate cancer, MILP can help to schedule the radiotherapy sessions taking into consideration the condition of the patient or available equipment for the therapy.

Although MILP is effective in numerous scheduling environments, constraint programming (CP) is a more flexible approach necessary to solve the scheduling problem as a constraint satisfaction problem. This is important in RT where the continuity of treatment intensity, the presence of patients with different treatment requirements, and changes in the state of patients (e.g., cancer progression) call for more fluidity. For example, lung cancer patients seen in a clinic are likely to have variations in their health status and therefore changes in the approaches of care and CP can appropriately address such dynamics (Pham et al., 2021). CP is especially useful for resolving complex scheduling problems with high uncertainty, for example, when there are contingencies to cater for emergencies or when some machines are taken for servicing (Narasimham, 2024). The use of both MILP and CP depends on computational capabilities and the nature of the scheduling problem being solved. Due to the complexity and interactivity of RT and the requirement of real time adjustment, there is a trend to combine the AI technology with deterministic model to enhance the efficiency of RT scheduling. Integrating AI into the existing MILP or CP models could optimize the treatment timetable and help in making timely changes in case of emergency, which also leads to enhanced patient care in cancer treatment centers (Alshamrani et al., 2024).

3.3. Stochastic and Robust Optimization

Stochastic and robust optimization solutions are important to provide solutions for the uncertainty factors related to the scheduling of RT, like the patient's arrival time, time to complete the treatment and available resources such as treatment machines, clinicians, treatment rooms, time slots, and support equipment. These uncertainties are modelled in Stochastic using probability distributions, thus allowing the formulation of robust schedules that allow for changes when they occur. This reduces interruptions since scheduling considers the variations of patient demands and efficiency or a new delay in completing the service by allowing for flexibility within the societies (Salari, Mazur and Sharp, 2023). Thus, by assessing the probabilities of certain outcome scenarios, stochastic optimization ensures high operational efficacy regardless of clinical uncertainties (Frimodig et al., 2023).

Schedule robustness models are developed based on non-probabilistic input parameters meaning that the resulting schedules are robust and can withstand worst cases that may include changes in patients' condition and machine breakdowns (Narasimham, 2024). Although this approach increases flexibility thereby incorporating variability in the model, it bears some disadvantages in that it may not capture all the variability that might occur in clinical practice because schedules may be disrupted by patients' health, and unpredictable availability of equipment, among other factors (Bian et al., 2023). The use of AI and ML with practical optimization has the potential to enhance online application adaptability, but there is a problem of scale, data scarcity and bias (Alshamrani et al., 2024). AI-based models rely on historical patterns and are not effective when facing rare events and unexpected interruptions in the clinical setting due to the reduced effectiveness related to their machine-learning nature (Smolders et al., 2024). However, despite the potential improvement of schedule accuracy through AI's application, AI remains challenging to implement in radiotherapy (RT) environments: data handling and clinician dependency on AI systems. Therefore, future studies need to identify and overcome these shortcomings while implementing the strategies in clinical practices that are clinically efficient and effective (Sonke et al., 2019).

3.4. Artificial Intelligence and Machine Learning Approaches

AI and ML are now significantly influencing the scheduling of radiotherapy in a way that improves decision-making and real-time optimization. One of the most promising approaches to AI optimization is reinforcement learning (RL), as it adapts during the time based on such factors as patient load, machine availability, or clinical constraints. RL adapts the scheduling techniques on its own with the help of the trial-and-error method, which enables constant changes to optimize the performance without delay (Fredriksson, Engwall and Andersson, 2021). This flexibility of RL makes it especially useful for addressing the nuances and chaos of actual clinical settings, while traditional optimization techniques may fall short of expectations (Ripsman et al., 2022). Self-teaching is another unique feature RL presents that makes it possible for RT scheduling systems to be much more efficient when they learn in real time.

Apart from RL, the other approaches that can be used in RT scheduling are neural networks (NNs) and deep learning (DL) models due to their refined prediction capacity. The two types of deep learning models are convolutional neural networks (CNNs) and recurrent neural networks (RNNs). These are most useful when dealing with large data and pattern recognition over time. While CNNs are good at modelling spatial features, RNNs are good at dealing with sequential data, thus enabling such models to capture temporal dependencies in aspects such as treatment planning and resource allocation (Visser et al., 2022). Using NNs and DL in RT scheduling enhances the predictive effectiveness of the scheduling process while assisting in the effective direction of resources and the enhancement of program operations Heath et al., 2021). Additional barriers relate to the interpretability, integration, and implementation of AI scheduling models, implying that much more study is needed to enhance the authenticity and feasibility of AI solutions in healthcare (Alshamrani et al., 2024).

4. Adaptive and Real-Time Scheduling in Radiotherapy

4.1. Concept of Adaptive Scheduling

Flexibility is a crucial factor that can be applied to the RT process to work with patient conditions, resources, and requirements in clinical practice environments, which can vary dynamically. Compared to other scheduling forms, such as pre-planned scheduling, rule-based scheduling, and heuristic scheduling, adaptive scheduling is more flexible in changing operations as it adapts to dynamic conditions on the field involving treatment plans. Some challenges that necessitate flexibility include tumour growth, changes in the patient's medical conditions, and sometimes equipment malfunctions that need to be addressed so that the time taken to administer treatment is as minimal as possible (Pham et al., 2021). The use of real-time data expansion take a more optimal approach by increasing the flexibility of adaptive scheduling and timely adaptability to schedule volatility to fit patient needs as well as clinical activities (Frimodig et al., 2023). Thus, the continuity of this approach, along with increasing

efficiency, contributes to better organization of interaction between the patient, clinician, and treatment resources to achieve the best results (Lavrova et al., 2023).
A patient-oriented approach to scheduling is more than logistical changes since it can involve addressing the treatment needs of individual patients. It addresses the issue of non-compliance with the recommended number of sessions by recognizing changes in patient outcomes and adapting the sessions' timing to exclude unnecessary waiting periods (Sonke et al., 2019). Several refined ways, such as AI and ML, include real-time modification of the treatment delivery schedule, which improves customization and management (Narasimham, 2024). Nevertheless, implementing adaptive scheduling in clinical practice raises questions like data integration, interprofessional relationships, and efficient models and methods that offer flexibility but are practicable (Alshamrani et al., 2024). As for future research, efforts should be directed towards further development of AI-based models to enhance the resource application's efficiency and patients' outcomes (Ten Eikelder et al., 2022).

4.2. Emerging Techniques for Real-Time Optimization

There are new innovative methods that improve real-time scheduling to readjust treatment plans due to unpredictability in patient's time, availability of machines and variation in treatment time. Online and rolling-horizon solutions are two mechanisms used to practice continuous updates based on real data. Online optimization allows the changes in the treatment planning as required for immediate changes, while rolling-horizon optimization refers to the changes in the schedules at regular intervals, enhancing the flexibility and effective use of resources (Frimodig et al., 2023; Pham et al., 2021). These methods help improve resource utilization and minimize extra time to make treatment processes effective and speedy, especially in busy medical practice settings. They can recalculate the schedule in real-time and ensure continuous RT operations, improving RT's efficiency. However, their application in hospital environments, in particular, has not reached widespread use because of the problems like computational requirements, data integration, the clinicians' reluctance, and implementation expenses (Lavrova, 2023 #34).
Besides these techniques, multi-agent systems are also growing popular to solve decentralized decision-making problems in real-time scheduling. These agents are aligned to work hand in hand to provide a proper treatment delivery, particularly when there is an intermapped disruption, such as equipment failure or an emergency. In addition, flexibility due to real-time rescheduling through predictive analytics and ML for scheduling adaptations due to potential disruptions is also beneficial for responsiveness (Lavrova et al., 2023; Ten Eikelder et al., 2022). In future studies, proactive real-time scheduling integrating decision support systems will be incorporated into artificial intelligence to improve scheduling precision, hospital clinical productivity, and patient care (Alshamrani et al., 2024).

4.3. Use of Big Data and Predictive Analytics

The application of big data and predictive analytics greatly impacts the RT scheduling process, improving the decision-making process based on real-time results. Hence, data-driven scheduling operates from patient file data, treatment times, and machine trends to create an efficient schedule that minimizes patient waiting times and better resource utilization (Frimodig et al., 2023). The obtained data sets allow the predictive models that show patterns and expected future variations in demand to avoid possible conflicts of schedules and improve cooperation (Pham et al., 2021). Using these insights, the RT departments can affordably allocate resources and avoid or mitigate disruptions more effectively such as machine breakdowns, emergency cases, a change in patients' schedule, variation in treatment times and other issues arising from the resource conflict. Moreover, other methods, such as real-time monitoring, help improve the scheduling since the availability of machines, patients, and the progress of treatment can be conducted continuously to make necessary adjustments to avoid any failure (Narasimham, 2024).

The incorporation of EHR is central in linking patient-specific information directly with scheduling systems so that clinicians can schedule to information and modify schedules according to changes in treatment progression or clinical priorities. Furthermore, there is improved usage of analytics and ML algorithms in scheduling to optimize the predictiveness of the scheduling models, making them patient-centric (Ten Eikelder et al., 2022). In further research, the focus should be on developing advanced AI technologies to utilize a great variety of real-time data to support clinic decisions, increase the accuracy of the scheduling, and increase clinic productivity and patient satisfaction (Alshamrani et al., 2024).

5. Challenges and Barriers to Implementation

5.1. Technical and Computational Challenges

Several technical such as MILP and CP, as well as computational challenges are associated with RT scheduling based on the nature of optimization models and the constraints of computational resources in decision-making. Optimization models should consider more factors like patient care priorities, equipment availability, and treatment limitations; thus, they are very complex and involve complex calculations (Frimodig et al., 2023). These technologies involve MILP and CP, which improve the scheduling efficiency but require substantial processing power; however, the increased demand for processing power hinders the scalability of scheduling systems, especially in large healthcare facilities (Pham et al., 2021). However, the outlined real-time schedule must include additional adaptiveness to various factors, including migration of patients' conditions and sudden interruptions that entail constant schedule calculations that augment computational demand (Lavrova et al., 2023).

However, challenges are likely to be encountered in the application of AI and ML for improving scheduling flexibility, such as speed limitations, data integration issues, and the requirement of a high-performance computing environment (Narasimham, 2024). There's still the issue of balancing between achieving higher scheduling accuracy and keeping the computations feasible to implement. Real-time scheduling can potentially benefit from cloud computing and distributed processing as part of its future research opportunities (Ten Eikelder et al., 2022). Future studies should be directed towards constructing lean, flexible models capable of managing timely and accurate data for practical implementations (Alshamrani et al., 2024).

5.2. Practical Barriers in Clinical Settings

The lack of practical automation in clinical environments also poses many difficulties in changing automated scheduling systems and artificial intelligence for RT. Automating tasks leads to various issues, including the credibility of the models incorporated in artificial intelligence. Many healthcare workers are concerned about the loss of clinical decision-making authority and believe it is better to use such systems as an aid while keeping most of the power with the clinician (Pham et al., 2021). This resistance stems from concerns regarding AI-driven solutions' ability to replicate the nuanced judgment typically applied by clinicians in making decisions on sensitive matters (Lavrova et al., 2023). Another factor that makes people skeptical of AI systems is the lack of visibility of the algorithms used in these systems, which is not suitable for clinical applications.

Another challenge is the integration of the AI algorithm in the scheduling system with other applications used in a hospital. Some best practices include collaboration with electronic health records (Roehrs et al.), treatment planning software, and hospital management systems to properly function the AI scheduling tools (Frimodig et al., 2023). Nevertheless, there are certain drawbacks including compatibility issues, data security issues, and the regulatory framework in which intelligent scheduling systems may not be fully feasible (Narasimham, 2024). In overcoming these barriers, interdisciplinary collaboration is necessary, as well as the strict integration of AI models into clinical practices that will not affect the workflow.

5.3. Ethical and Patient-Centric Considerations

Ethical and patient-related aspects also shape RT scheduling immensely and avoid compromising the noble goal of efficiency with poor patient outcomes. Scheduling is one of the most significant issues, and it should be optimized to minimize appointment gaps and not overuse resources while providing more personalized plans (Pham et al., 2021). Automated scheduling solutions are supposed to help optimize workflows; nonetheless, such systems should not demethylise patients or decrease clinicians' monitoring, which remains significant in addressing patients’ bio-psychosocial needs (Lavrova et al., 2023). It is important to note that this balance should be achieved to ensure that the tools assist in the clinical work instead of impersonating clinical decisions.

It is equally important to be impartial in the distribution of schedules since all patients deserve equal treatment to get the best services they need and deserve. The scheduling algorithm should justify clinical needs, eliminating patient prioritization biases (Frimodig et al., 2023; Narasimham, 2024). Compliance with the scheduling processes also helps to maintain patient trust and reduce the overall anxiety related to the further course of treatment (Alshamrani et al., 2024).

6. Conclusion

In conclusion, the implementation of adaptive scheduling and optimization in the scheduling of radiotherapy (RT) has the potential of improving efficiency, effectiveness, and quality of the treatment significantly. The complexity of RT’s environment makes strategies like MILP and CP inadequate, which are still great for solving more structured problems. AI methods, including RL and ML, have better flexibility and real-time decision-making regarding patient’s condition fluctuation, equipment malfunctioning, or any kind of disturbances. However, some problems like computational requirements, interfacing, and clinician endorsement are some of the concerns that need to be considered. The future direction seems to be the integration of AI solutions with the existing models, the implementation of the interdisciplinary approach, and integration of the beneficial concepts to the clinical practices and patients’ care.

7. Future Directions and Research Gaps

Improving the flow of RT scheduling means developing strategies to make the process more efficient, even though it must be patient-centred. A new approach to optimizing scheduling is using hybrid models based on deterministic models and the application of AI optimization methods, which coordinates the benefits of rigid structures with the flexibility of application.

Multi-objective optimization extends scheduling to ensure fair distribution of treatment based on the availability of resources while simultaneously seeking to maximize the use of resources. Computer-based simulation has been thought to be a good approach to providing personalized care plans. They also enable clinicians to try several scheduling possibilities before the process begins to minimize delays and increase the accuracy of care delivery. Moreover, federated learning allows building AI models that can be trained on the data collected by various healthcare facilities simultaneously to develop more generalizable solutions to scheduling problems while ensuring data privacy. However, these advanced techniques need policy formation and standards, interfacing scheduling systems integrated with EHR, and compliance with regulatory norms. Unifying frameworks for RT scheduling will simplify adoption processes, facilitate collaboration between institutions, and maintain consistent patient treatment. Future studies should continue to develop these models in addition to evaluating interdisciplinary relationships and international guidelines for RT scheduling.

References

Alshamrani, A., Aznar, M., Hoskin, P., Chuter, R., & Eccles, C. L. (2024). The current use of adaptive strategies for external beam radiotherapy in cervical cancer: a systematic review. *Clinical Oncology*, *36*(12), e483-e493.

Åström, L. M., Behrens, C. P., Calmels, L., Sjöström, D., Geertsen, P., Mouritsen, L. S., ... & Sibolt, P. (2022). Online adaptive radiotherapy of urinary bladder cancer with full re-optimization to the anatomy of the day: Initial experience and dosimetric benefits. *Radiotherapy and Oncology*, *171*, 37-42.

Bian, F., Liu, J., Zhang, X., Gao, H., & Cai, J. F. (2023). Stochastic Three-Operator Splitting Algorithms for Nonconvex and Nonsmooth Optimization Arising from FLASH Radiotherapy. *arXiv preprint arXiv:2311.14292*.

Braune, R., Gutjahr, W. J., & Vogl, P. (2022). Stochastic radiotherapy appointment scheduling. *Central European Journal of Operations Research*, 1-39.

Dona Lemus, O. M., Cao, M., Cai, B., Cummings, M., & Zheng, D. (2024). Adaptive radiotherapy: next-generation radiotherapy. *Cancers*, *16*(6), 1206.

Emsamrit, N., & Boonmee, C. (2024). Mixed-Integer Linear programming for scheduling of radiotherapy patients. *Engineering and Applied Science Research*, *51*(1), 106-116.

Ferini, G., Molino, L., Bottalico, L., De Lucia, P., & Garofalo, F. (2021). A small case series about safety and effectiveness of a hypofractionated electron beam radiotherapy schedule in five fractions for facial non melanoma skin cancer among frail and elderly patients. *reports of practical Oncology and radiotherapy*, *26*(1), 66-72.

Fredriksson, A., Engwall, E., & Andersson, B. (2021). Robust radiation therapy optimization using simulated treatment courses for handling deformable organ motion. *Physics in Medicine & Biology*, *66*(4), 045010.

Frimodig, S., Enqvist, P., Carlsson, M., & Mercier, C. (2023). Comparing optimization methods for radiation therapy patient scheduling using different objectives. Operations Research Forum,

Galluzzi, L., Aryankalayil, M. J., Coleman, C. N., & Formenti, S. C. (2023). Emerging evidence for adapting radiotherapy to immunotherapy. *Nature reviews Clinical oncology*, *20*(8), 543-557.

Garriga, R., Mas, J., Abraha, S., Nolan, J., Harrison, O., Tadros, G., & Matic, A. (2022). Machine learning model to predict mental health crises from electronic health records. *Nature medicine*, *28*(6), 1240-1248.

Glide-Hurst, C. K., Lee, P., Yock, A. D., Olsen, J. R., Cao, M., Siddiqui, F., Parker, W., Doemer, A., Rong, Y., & Kishan, A. U. (2021). Adaptive radiation therapy (ART) strategies and technical considerations: a state of the ART review from NRG oncology. *International Journal of Radiation Oncology* Biology* Physics*, *109*(4), 1054-1075.

Heath, E., Mueller, S., Guyer, G., Duetschler, A., Elicin, O., Aebersold, D., ... & Manser, P. (2021). Implementation and experimental validation of a robust hybrid direct aperture optimization approach for mixed-beam radiotherapy. *Medical physics*, *48*(11), 7299-7312.

Huang, P., Shang, J., Xie, X., Hu, Z., Liu, Z., & Yan, H. (2024). Applying mixed-integer linear programming to the non-coplanar beam angle optimization of intensity-modulated radiotherapy for liver cancer. *Quantitative Imaging in Medicine and Surgery*, *14*(8), 5789.

Jeyakumar, V., Li, G., Woolnough, D., & Wu, H. (2024). Affinely adjustable robust optimization for radiation therapy under evolving data uncertainty via semi-definite programming. *Optimization*, *73*(6), 1807-1832.

Lavrova, E., Garrett, M. D., Wang, Y.-F., Chin, C., Elliston, C., Savacool, M., Price, M., Kachnic, L. A., & Horowitz, D. P. (2023). Adaptive radiation therapy: A review of CT-based techniques. *Radiology: Imaging Cancer*, *5*(4), e230011.

Narasimham, N. (2024). Biomimicry in Radiation Therapy: Optimizing Patient Scheduling for Improved Treatment Outcomes. *arXiv preprint arXiv:2404.09996*.

Niraula, D., Sun, W., Jin, J., Dinov, I. D., Cuneo, K., Jamaluddin, J., ... & El Naqa, I. (2023). A clinical decision support system for AI-assisted decision-making in response-adaptive radiotherapy (ARCliDS). *Scientific Reports*, *13*(1), 5279.

Pham, D., Roxby, P., Kron, T., Rolfo, A., & Foroudi, F. (2013). Introduction of online adaptive radiotherapy for bladder cancer through a multicentre clinical trial (Trans-Tasman Radiation Oncology Group 10.01): Lessons learned. *Journal of Medical Physics*, *38*(2), 59-66.

Pham, T.-S., Legrain, A., De Causmaecker, P., & Rousseau, L.-M. (2021). A prediction-based approach for online dynamic patient scheduling: a case study in radiotherapy treatment. *arXiv preprint arXiv:2112.08549*.

Piperdi, H., Portal, D., Neibart, S. S., Yue, N. J., Jabbour, S. K., & Reyhan, M. (2021). Adaptive radiation therapy in the treatment of lung cancer: an overview of the current state of the field. *Frontiers in Oncology*, *11*, 770382.

Rigaud, B., Anderson, B. M., Zhiqian, H. Y., Gobeli, M., Cazoulat, G., Söderberg, J., ... & Brock, K. K. (2021). Automatic segmentation using deep learning to enable online dose optimization during adaptive radiation therapy of cervical cancer. *International Journal of Radiation Oncology* Biology* Physics*, *109*(4), 1096-1110.

Ripsman, D. A., Purdie, T. G., Chan, T. C., & Mahmoudzadeh, H. (2022). Robust direct aperture optimization for radiation therapy treatment planning. *INFORMS Journal on Computing*, *34*(4), 2017-2038.

Roehrs, A., Da Costa, C. A., da Rosa Righi, R., & De Oliveira, K. S. F. (2017). Personal health records: a systematic literature review. *Journal of medical Internet research*, *19*(1), e5876.

Salari, E., Mazur, T., & Sharp, G. (2023). A stochastic control approach to intrafraction motion management in intensity-modulated radiotherapy. *Physics in Medicine & Biology*, *68*(8), 085020.

Shinde, N., Zhang, W., Lin, Y., & Gao, H. (2025). A mixed integer programming approach to minibeam aperture optimization for multi-collimator proton minibeam radiotherapy. *arXiv preprint arXiv:2502.16326*.

Smolders, A., Bengtsson, I., Forsgren, A., Lomax, A., Weber, D. C., Fredriksson, A., & Albertini, F. (2024). Robust optimization strategies for contour uncertainties in online adaptive radiation therapy. *Physics in Medicine & Biology*, *69*(16), 165001.

Sonke, J.-J., Aznar, M., & Rasch, C. (2019). Adaptive radiotherapy for anatomical changes. Seminars in radiation oncology,

Ten Eikelder, S., Ajdari, A., Bortfeld, T., & den Hertog, D. (2022). Adjustable robust treatment-length optimization in radiation therapy. *Optimization and Engineering*, *23*(4), 1949-1986.

Vieira, B., Demirtas, D., van de Kamer, J. B., Hans, E. W., Jongste, W., & van Harten, W. (2021). Radiotherapy treatment scheduling: Implementing operations research into clinical practice. *Plos one*, *16*(2), e0247428.

Visser, S., Ribeiro, C. O., Dieters, M., Mul, V. E., Niezink, A. G., van der Schaaf, A., ... & Muijs, C. T. (2022). Robustness assessment of clinical adaptive proton and photon radiotherapy for oesophageal cancer in the model-based approach. *Radiotherapy and Oncology*, *177*, 197-204.

Wang, H., Liu, X., Song, Y., Yin, P., Zou, J., Shi, X., ... & Li, Z. (2023). Feasibility study of adaptive radiotherapy for esophageal cancer using artificial intelligence autosegmentation based on MR-Linac. *Frontiers in Oncology*, *13*, 1172135.

Yoganathan, S. A., Khemissi, A., Paloor, S., Hammoud, R., & Al-Hammadi, N. (2025). An End-to-end Quality Assurance Procedure for Ethos Online Adaptive Radiotherapy. *Journal of Medical Physics*, *50*(1), 140-147.

Zhong, H., Adams, J., Glide-Hurst, C., Zhang, H., Li, H., & Chetty, I. J. (2016). Development of a deformable dosimetric phantom to verify dose accumulation algorithms for adaptive radiotherapy. *Journal of Medical Physics*, *41*(2), 106-114.