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EXPLORING STOCHASTIC MODELING AND SYSTEM DYNAMICS FOR HEALTHCARE OPTIMIZATION: LESSONS FOR RADIOTHERAPY SCHEDULING

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Abstract

Background: All Radiotherapy schedules are designed to maximise tumour control probability and minimise normal healthy tissue complications. However, the rapidly growing demand for radiotherapy services, coupled with limited resources, poorly scheduled appointments, and increasing complexities of cases, is urgently demanding more advanced systems and models to optimise the efficiency of radiotherapy treatments around the world. This is further complicated by unplanned gaps leading to significant scheduling challenges.

Materials and Methods: This paper focuses on stochastic processes, system dynamics, and artificial intelligence (AI) for radiotherapy scheduling. It utilises a systematic literature review concerning scheduling methodologies that embrace Markov chains, Monte Carlo methods, queuing systems, and their hybrids. The review sought literature to control patient flow, resource control, and adaptable systems.

Results: Stochastic models were found to promote better utilisation of resources by improving patient flow, reducing machine idle time, and enhancing resource utilisation. Adaptive scheduling approaches and system dynamic models enable better workforce planning, reduce idle time, and minimise the disruptions of various business processes. AI-info trick analytics further enhance scheduling accuracy by making arrivals and equipment downtime forecasts to refine resource scheduling approaches. Stochastic approaches to system dynamic modelling offer a holistic way to solve practical scheduling problems.

Conclusion: Advanced scheduling techniques, especially hybrid ones, can enhance resource allocation and reduce treatment delays for radiotherapy patients. Future studies should focus on integrating electronic health records (EHRs) with active patient monitoring to augment scheduling accuracy. Such approaches will increase treatment and service delivery efficacy in radiotherapy centres through a real-time patient data-capturing model while ensuring that all patients receive equally effective treatment.

Keywords: Radiotherapy Scheduling, Stochastic Modeling, System Dynamics, Artificial Intelligence, Patient Flow Optimization.

Introduction

Radiotherapy is a radiation-based cancer treatment that aims at damaging as much cancer tissue as possible with minimal interactions with surrounding healthy tissues [1]. It is a core aspect of cancer treatment because almost 50% of all patients suffering from any malignant tumour undergo it at some stage of their treatment [2]. The central aspect of the radiotherapy process is delivering ionizing radiations such as x-rays, gamma rays or even protons to the tumour area, where cancer cells will have their DNA molecule cleaved [3]. This improperly repaired DNA will hinder cell divisions, causing the targeted cells to die. While normal cells are susceptible to damage, they can self-fix more efficiently than malignant ones so that radiotherapy can be effectively employed [4]. Treatment schedules must be carefully planned to maximize the effectiveness of radiotherapy. Proper timing and dosage are critical, as malignant cells must be irradiated at specific intervals that prevent their regeneration, ensuring the best possible therapeutic outcomes for patients with various malignancies.

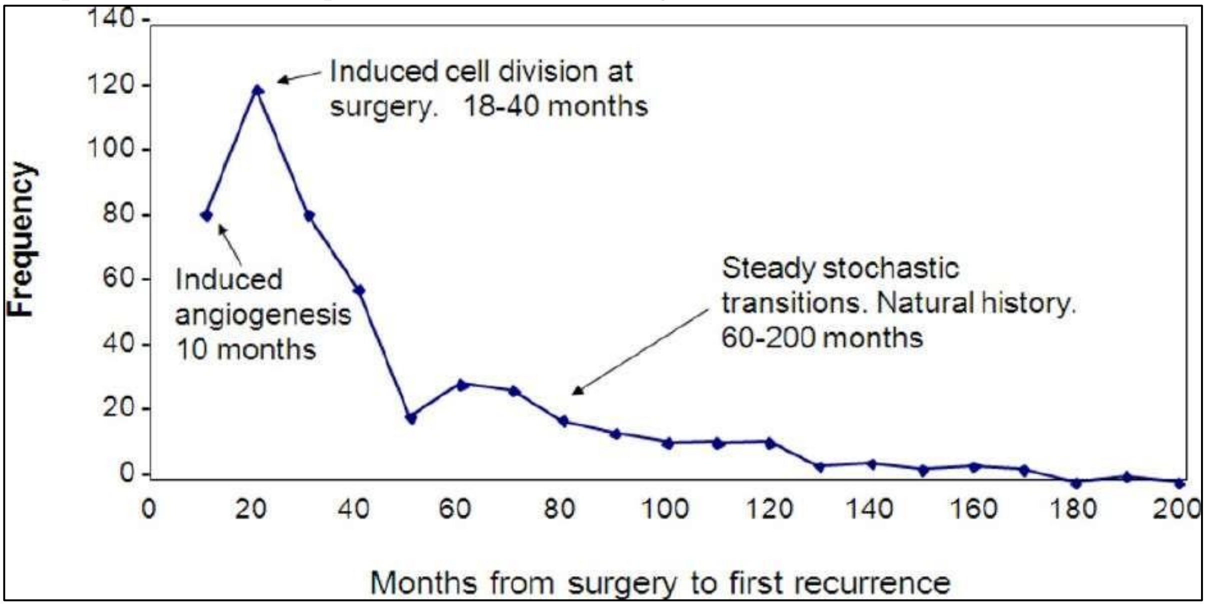

Figure 1: Breast cancer treatment [58]

Scheduling refers to the allocation of resources to achieve targets and goals. Within the radiotherapy workflow, the initial step involves a consultation with the patient, followed by a reservation of time blocks for both CT simulations and Treatment delivery [5]. Before actual treatment, CT simulation is done, which consists of imaging the region of interest. These images reflect the tumour and consider the patient's health and other concurrent affairs, as well as the size and location of the tumour, alongside the parameters of treatment that have already been decided [6]. Patients have prioritization based on the urgency of the treatment, in which high-priority cases require immediate attention, whereas lower-priority patients can wait for days to even weeks. Effectively, scheduling and coordinating the variety of consultations, CT simulations, and linear accelerator treatments presents quite a few challenges. The primary constraint within treatments is the availability of linear accelerators, which oftentimes results in long queues [7]. Other clinics differ regarding treatment protocols, fractionation schemes, and scheduling frameworks. A more compelling aspect comes with the variability in the length of procedures and patients' arrival times, which all impact the schedule and make it necessary to fluctuate to reduce the burden on resources.

Precision regarding radiotherapy treatment schedules should be observed to achieve optimal therapeutic outcomes for patients with malignancy. The malignant cells must be irradiated at specific intervals that would not allow regeneration [8]. Treatment is delivered in several fractions, usually over several weeks, to ensure a sufficient dose to destroy as many cancer cells as possible while allowing other tissues to recuperate [9]. However, maintaining proper adherence during the schedule is imperative to achieve the intended results of the radiotherapy, which is nevertheless unfortunate. The radiotherapy schedule is notoriously difficult to organize because several factors must be managed simultaneously [10]. Each patient has a treatment plan based on many clinical parameters like the tumour type, size, disease stage, and overall patient condition. Moreover, the radiotherapy treatment is usually delivered in several fractions over several weeks, each meticulously crafted to give the appropriate radiation dosage at the correct time [11]. Thus, patients' appointments need to be scheduled with the limited availability of radiotherapy machines, which are expensive and in high demand. The scarcity of machines in most healthcare institutions makes the scheduling even more challenging because there are numerous patients with different types of cancers, each of whom has varied lengths and frequencies of needed treatments [12].
Another significant barrier to planning radiotherapy treatment is the interventions of any ad hoc disturbance. An equipment breakdown creates idle time for machines and unscheduled cancellations of assigned slots. Repair procedures and maintenance activities, which are lengthy given the high engineering sophistication of radiotherapy devices, result in treatment delays for several patients. Moreover, sometimes, additional conditions treatable with radiotherapy use up slots that had already been booked, meaning those patients needing immediate attention are prioritized, and the routine work is redone [13]. The need for such changes makes logic and reasoning more complicated, as healthcare systems resource providers need to find other strategies to alter patient case and appointment schedules that would incur delays that are not extended. Effectively addressing these requirements is critical to preventing negative implications in treatment outcomes, as there is an optimal number of treatment sessions beyond which the system's effectiveness diminishes.
Treatment delays impact radiotherapy differently; however, it is an extensively studied issue, and one delay can worsen a patient's outcome. For instance, the studies conducted on head and neck cancer patients discovered that a mere 1-week treatment delay resulted in a 2% decrease in local control rates [14]. As a result, there is no control of the tumour in the targeted body region, which gets increasingly vulnerable to cancerous growth [15]. Such delays are concerning for aggressive cancers as even a slight alteration in the treatment regimen can considerably impact survival. These factors illustrate the risk of not promptly delivering radiotherapy, which stems from scheduling inefficiencies and can cause significant clinical consequences. The data indicates that more than five days of interruption during breast cancer radiotherapy can cause local recurrence rates to increase by over 20% [16]. This correlates to how vital the care continuum is in radiotherapy. With the breaks, the cancer cells might start repairing themselves from the radiation damage, which can severely reduce the effectiveness of future radiation doses [17]. This might increase the possibility of tumours reappearing, which would then increase the need for control measures like surgery or chemotherapy, which further aggravates the patient's care needs. Concerns about these delays' negative impact are heightened because they seek to hinder the primary objective of effective radiotherapy, which is to destroy cancer cells while preserving healthy tissues.

As a result of treatment postponements and scheduling inefficiencies, desired health outcomes are difficult to achieve. The need to formulate advanced models for scheduling radiotherapy is of great importance. Hospitals can enhance the distribution of machine time, plan for machine breakdowns, and create other plans to minimise delays using mathematical and computational models. Models can also be built from real-time data on machine use, patient requirements, and potential emergencies, enhancing the scheduling decisions' reliability to mitigate prolonged interruptions [18]. Stochastic modelling has found vast applications in the healthcare sector as it improves decision-making and, as a result, deepens one's proficiency in handling uncertainties [19]. In the highly stochastic nature of radiotherapy, where many things are not controllable, stochastic models enhance inefficiency in scheduling and patient arrival and address many other problems [20]. The application of key stochastic modelling techniques in healthcare optimisation is unprecedented, but optimists believe these approaches will lead to better organisation and productivity.
The Markov model is one such method that has been applied extensively for simulating disease progression and evaluating the effectiveness of treatments over long periods [19]. Markov models function by portraying a system as a set of states, which change based on specific probabilities [21]. In radiotherapy, Markov models enable healthcare professionals to estimate disease progression at various treatment intervals and assess how different scheduling lapses or changes impact the chances of survival [22]. These models are instrumental in oncology for treatment planning since they offer a way of estimating and comparing different treatment methods and selecting the appropriate one that optimises the patient's outcome.
Monte Carlo simulations differ from Traditional stochastic modelling in that random variables are incorporated to pull real-world scenarios to evaluate and create many potential situations. In radiotherapy, these studies enable one to conduct distinct analyses, such as examining how patient attendance, appointment allocations, and equipment availability influence treatment strategies' total effectiveness [23]. With these simulations and games, healthcare management can run hundreds, thousands, or even millions of simulations to determine the likelihood of specific scheduling problems and find the best strategies to deal with the delays [24]. This method supports determining the risks to be taken because the decision maker captures the scope of minimum delays on the checkup and takes measures to avert the situation [25]. Queuing theory is yet another stochastic modelling technique applied extensively in optimising service delivery in the healthcare sector, especially in radiotherapy centres [26]. This framework relies on mathematics to streamline the flow of patients into a system and out of it by using the elements of arrival, service, and departure. In radiotherapy centres, queuing theory reduces patient idle time while maximising available resources by effectively scheduling appointments and controlling machine usage [27]. Healthcare facilities can study historical patient flow data to determine if there are delays in providing treatment and devise measures to minimise the congestion. Research has demonstrated that average waiting times in radiotherapy centres can be reduced by 67% through queuing theory, significantly improving service efficiency [28]. This enhances a patient's experience and guarantees that treatments are carried out within clinically advisable durations to avert adverse effects on the patient's health due to overly deferring treatment [28]. With the application of Markov chains, Monte Carlo simulations and other queuing systems integrated into the scheduling of radiotherapy, healthcare providers can manage patient uncertainties while achieving better healthcare results. System Dynamics captures a magnified view of the mechanics of healthcare operations by

modelling many feedback loops and interdependencies in the healthcare system, which can often be considered multidimensional [29]. This has been widely used in the healthcare sector to study patient flow patterns, use of available resources properly, and compliance with treatment regimens. Models of System Dynamics utilize causal loop diagrams to illustrate interrelations among core metrics and stock-and-flow diagrams to depict the capturing and dispersal of resources [30]. The simulation models based on System Dynamics provide the ability to analyze different scenarios and enable healthcare managers to judge the effects of varying scheduling methods on the system's performance. Research suggests that system dynamics approaches to radiotherapy treatment scheduling can improve patient throughput by as much as 85% while minimizing treatment delays [31]. Moreover, System Dynamics simulations have been crucial in evaluating radiotherapy workforce planning strategies to maximize the active use of radiotherapy staff and facilities.

The combination of stochastic modelling and system dynamics provides an all-encompassing approach to improving the scheduling of radiotherapy by utilizing the best of both methods [32]. Stochastic models capture the details of patient inflow, the expected treatment time, and the likelihood of equipment failures. In contrast, System Dynamics models capture the holistic view of the entire healthcare system [33]. Using these approaches allows healthcare providers to set up robust scheduling controls that can respond to uncertainties and reduce disruptions to treatment. Other studies confirm that applying a combination of stochastic modelling and System Dynamics improves patient flow by up to thirty per cent while enhancing overall resource utilization through an increase in efficient treatment delivery [34].

The performance of radiotherapy scheduling has also greatly benefitted from implementing hybrid models that combine stochastic and System Dynamics approaches. Hybrid models facilitate the creation of adaptive scheduling systems capable of real-time treatment plan modifications depending on the prevailing clinical situation and resources [35]. Reinforcement learning and increased reliance on AI-powered stochastic optimization have improved the predictive power of these models and made scheduling modifications more accurate. Recent publications have reported the successful deployment of AI-powered stochastic models to predict and prevent machine breakdowns, thereby increasing the productivity of the equipment and ensuring uninterrupted treatment provision [36]. Undoubtedly, the need for effective scheduling services continues to heighten due to the expanding demand for radiotherapy services alongside the ease of complexity in treatment regimens. The application of data derived stochastic modelling and System Dynamics approaches offers the potential to turn radiotherapy scheduling inpatient therapy optimization into a reality, which would invariably improve the efficacy of the healthcare system [37]. Such approaches enable healthcare managers to create advanced scheduling systems with a proactive approach geared towards improving service provision while reducing costs associated with cancer care. Further studies should consider enhancing the delivery of radiotherapy services by networked multi-facility healthcare systems through further refinements to these models using active patient data.

This research analyses the uses of stochastic modelling and System Dynamics, especially in scheduling radiotherapy. This review aims to determine how these methodologies can be synergized to alleviate scheduling and treatment disruptions. The central hypothesis is that combining stochastic modelling and system dynamics will significantly improve the decision-making process in the radiotherapy schedule. This should increase the use of available resources, decrease patient waiting time, and improve results. Through real-world study examples and a literature review, this research aims to understand how effective these advanced modelling techniques would be in radiotherapy. Healthcare systems must constantly evolve to overcome challenges related to uncertainty, resource limitations, and increasing patient expectations. Stochastic modelling and System Dynamics are compelling in optimizing healthcare operations, such as scheduling radiotherapy. Combining these two approaches allows clinicians to design more robust and effective scheduling systems, improving patient satisfaction and overall health outcomes. Existing studies have shown that the effectiveness of the systems can be enhanced, machine idle time reduced, and patient satisfaction increased with the application of these techniques in radiotherapy scheduling. This research will address the knowledge gap in optimizing healthcare services by exploring the application of stochastic modelling and System Dynamics in radiotherapy scheduling for their clinical practice adoption.

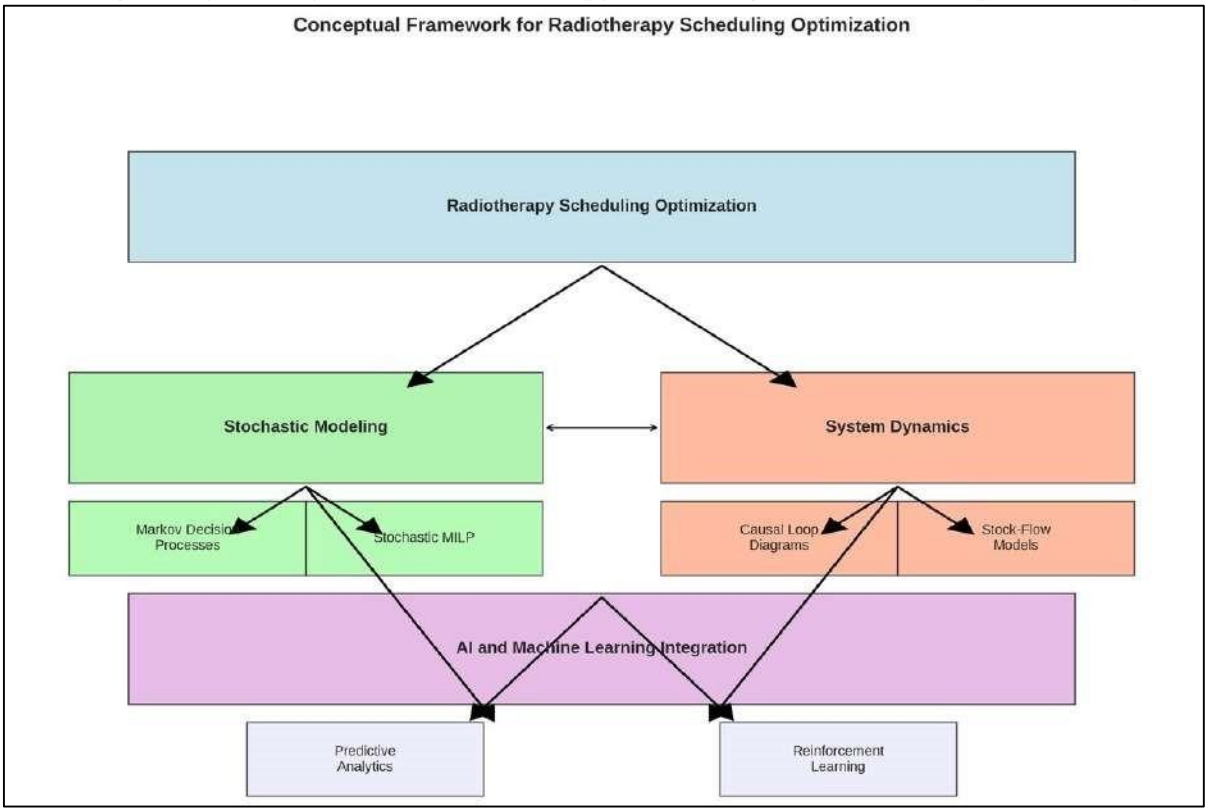

Figure 2: Conceptual framework

Theoretical Foundations

Markov Decision Processes (MDPs), queuing theory, and Monte Carlo considerations are radiotherapy scheduling models whose mathematical formulations have laid a fundamental basis upon which healthcare delivery can be optimized [38]. Non-specialists might have difficulty understanding how relevant they are in clinical situations. To sort this out, important theoretical terms should be related to practice. For example, in MDPs, the discount factor (gamma) is essential because it balances short- and long-term decision-making well. A small γ focuses on short-term clinical realities, like the requirement to support high-priority cancer patients. In contrast, a large γ captures the long-term significance of system efficiency, such as reducing the number of treatment delays [39]. This definition fills the scholastic vacuum between theoretical optimization and its practical sequencers in hospitals.

In addition, the synergy of stochastic modelling and System Dynamics (SD) is essential in comprehending the entire spectrum of radiotherapy scheduling solutions. Queuing systems, Monte Carlo simulations, Markov chains, and other stochastic models are most suitable for making operational judgments in imperfect conditions [40]. They manage volatile situations such as patient no-shows, random treatment lengths and equipment outages, allowing them to allocate resources responsively based on data.

Conversely, System Dynamics is superior at analyzing structural and higher-level policy problems by modelling feedback loops and long-term trends. For example, SD can directly show how bottlenecks in the treatment process run along delayed recruitment or budget limitations over time. At scale, these methods can combine to become hybrid approaches, which provides an even more considerable advantage: immediate variability is handled by stochastic manipulation, whereas SD considers the context of the system [41]. Hybrid approaches are better than single approaches for short-term turmoil and long-term structural inefficiency. To go deeper in improving scheduling, AI, especially Reinforcement Learning (RL), has demonstrated desirable outcomes. A case presented a good example at Memorial Sloan Kettering Cancer Center; RL algorithms were used in planning radiotherapy [42]. This historical-based patient and treatment modelled systems could increase treatment duration prediction rate by 25% to 87% and assign time slots and equipment better. This minimized patient waiting time and boosted throughput and overall patient outcomes. These frameworks, stochastic modelling, System Dynamics, and AI, can be combined to provide the complete radiotherapy scheduling toolset. When combined, their respective use can improve the reliability of operations and the robustness of cancer care delivery strategies at large, eventually advancing more streamlined, fair, and efficient care routes.

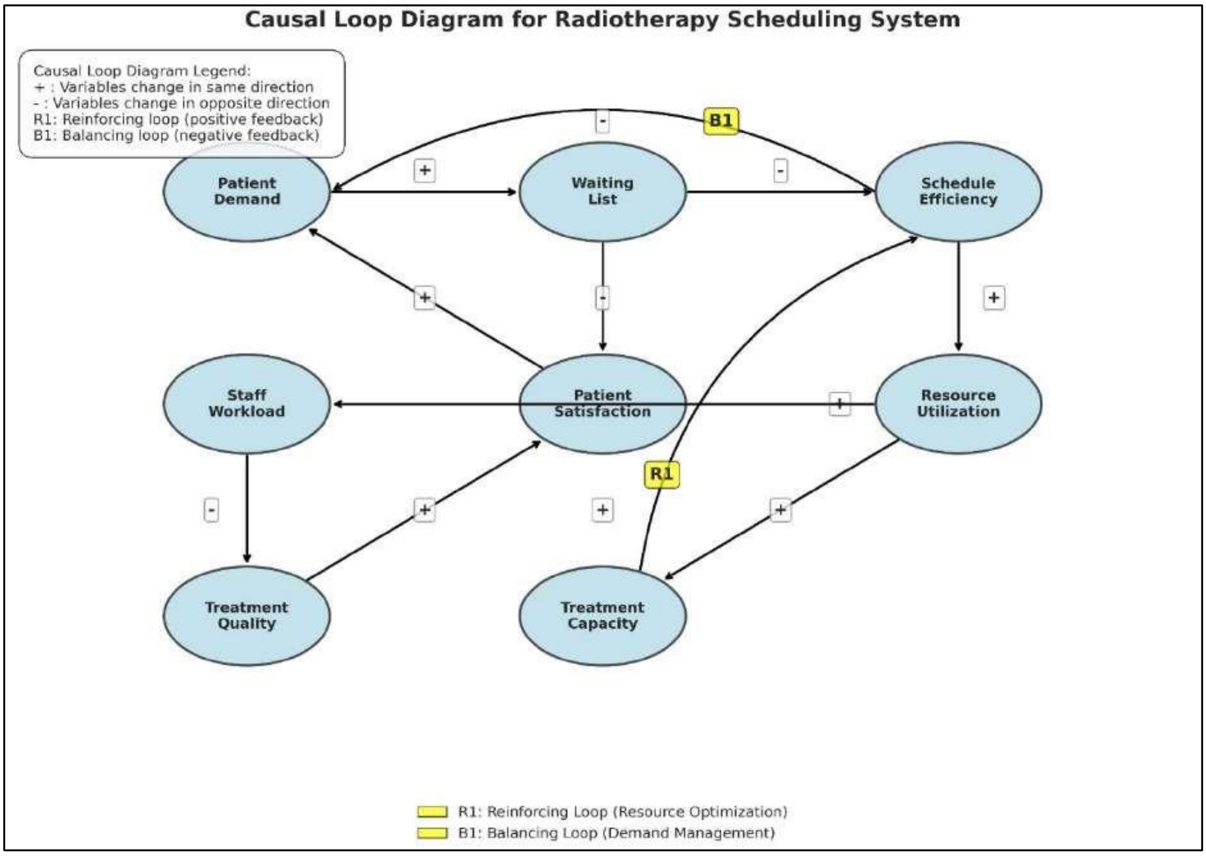

Figure 3: Radiotherapy scheduling system

Materials and Methods

In this research, the author uses the systematic literature review methodology to explore dynamic systems modelling and stochastic modelling techniques that have been applied to optimise the delivery of healthcare services and, specifically, how they have been used in scheduling radiotherapy. The review protocol was set to assure transparency, methodological rigour and reproducibility following the PRISMA guidelines (Preferred Reporting Items for Systematic Reviews and Meta-Analyses). The general objective is to synthesise the studies' trends, innovations, and performance outcomes to determine the best practices and inform future research.

Database and Search Strategy

Four scholarly databases, including PubMed, IEEE Xplore, ScienceDirect and Google Scholar, were used to conduct the literature search. Structured Boolean methodology was applied, which involved the combination of various terms such as stochastic modelling, system dynamics, healthcare optimisation, radiotherapy scheduling, queuing theory, Monte Carlo simulation, resource allocation, and patient flow management. These keywords have been selected to include theoretical models and applied frameworks in healthcare operations. The articles retrieved were restricted to articles published only in 2019-2024 to ensure that they reflected the current developments in the use of hybrid and the application of AI-based approaches. Peerreviewed journal articles and conference proceedings were only considered, as they are more on the academic side and of interest.

Eligibility Criteria

Quality inclusion criteria were established to ensure direct targeting of stochastic or system dynamics modelling applications to radiotherapy scheduling or related healthcare operations and closely related topics. Studies considered eligible were required to exhibit objective results, e.g. reductions in waiting time, machine utilisation, enhancement of therapy efficiency, etc., and simulation-based empirical processes, including queuing theory, Markov process or agentbased modelling [43]. The exclusion criteria excluded those studies that only described healthcare optimisation abstractly, did not have practical applications, or were not published earlier than 2019. Articles that did proportional economic analyses and not on the operational efficiency were also reduced, as well as purely theoretical papers that failed to mention the validation of the models or empirical tests.

Selection and Data Extraction of Study

All the titles and abstracts were later screened by a panel of eight reviewers independently against the eligibility criteria after removing the duplicate titles. The articles that survived this first sieve were reviewed in full text to check their relevance and merit in the methods applied. When there was a disagreement, then decisions were reached by group discussion. In cases where a conciliatory decision could not be arrived at, then the third-party reviewer consulted would provide an objective solution. The PRISMA flow diagram (Figure 1 in the complete report) gives an overview of the search and inclusion process to put the magnitude of the review into perspective.

Evolution of Methodologies Over Time

One of the trends revealed in the literature is that the methodological approach to radiotherapy scheduling has evolved over the last twenty years. Between 2000 and 2010, the most popular models were purely stochastic, including queuing theory, Markov chains, and Monte Carlo simulations. These methods concentrated on unpredictability and volatility in patient arrival times, resourceun grooming, and treatment times, providing detailed control of operational processes. From 2010 to 2015, the period marked a more focused approach to System Dynamics (SD) modelling, which sought more system-wide views on healthcare bottlenecks, feedback loops, and policy implications.

By 2015, researchers had started combining the two approaches, and hybrid models were developed that could be used to capture short-term variability and long-term system structure at the same time. Since 2020 and until 2025, AI-enhanced methods have been developed, such as reinforcement learning, predictive modelling, and real-time scheduling systems based on machine learning [44]. Historic-based models use historical data to give adaptive solutions that can react to real-time alterations in clinical conditions. Figure 2 (Methodological Timeline) displays the chronological development of such approaches, providing insight into the visual development of the discipline towards more intelligent and responsive optimisation frameworks.

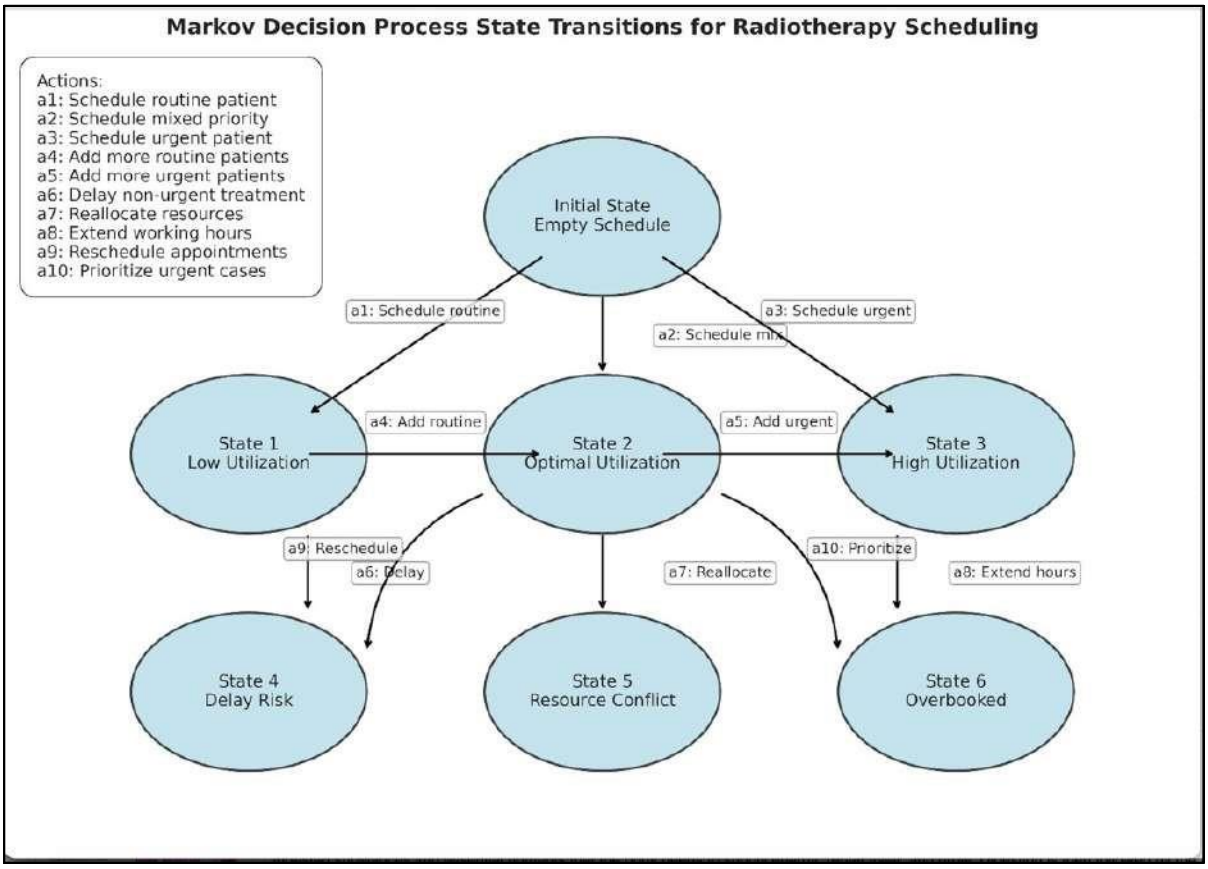

Figure 4: Transition of Radiotherapy scheduling

Comparative Analysis Methodology

Considering the variety of the metrics available in the chosen studies, which summarized the waiting time of patients to machine idle rates and treatment throughput, an explicit standardization procedure was required to provide any comparison of the studies. First,

normalized outcomes were calculated using Z-scores and percentage change of baseline to compare results obtained in different units (e.g., minutes, hours) and based on a standardized scale [45]. To illustrate, a 20% decrease in patient wait time and a 10% increase in throughput may not form a very small or large effect size but could be usefully compared by computing the effect size.
Where a study employed incompatible metrics, unit conversion formulas were used to compare measurements. For example, the time it may take to be delayed was reported in days, which were translated into hours based on average clinic operating hours to capture the equipment utilization rate [46]. In cases where quantitative conversion has not been possible, three healthcare operations experts were selected to independently review and rate the effects of the intervention on a standardized 5-pt scale, given the clinical relevance, operational feasibility, and all the reported outcomes.
A weighted aggregation formula was ultimately applied to generate a compounding score for each study. This expression placed a 60% weight on normalized quantitative data, a 30% weight on expert panel ratings, and a 10% weight on methodological rigour (e.g., the size of the sample and simulation fidelity). The mixed method enabled a consistent, even, and open weighting of different studies—the ones that provided the most feasible and scalable solutions to radiotherapy scheduling.

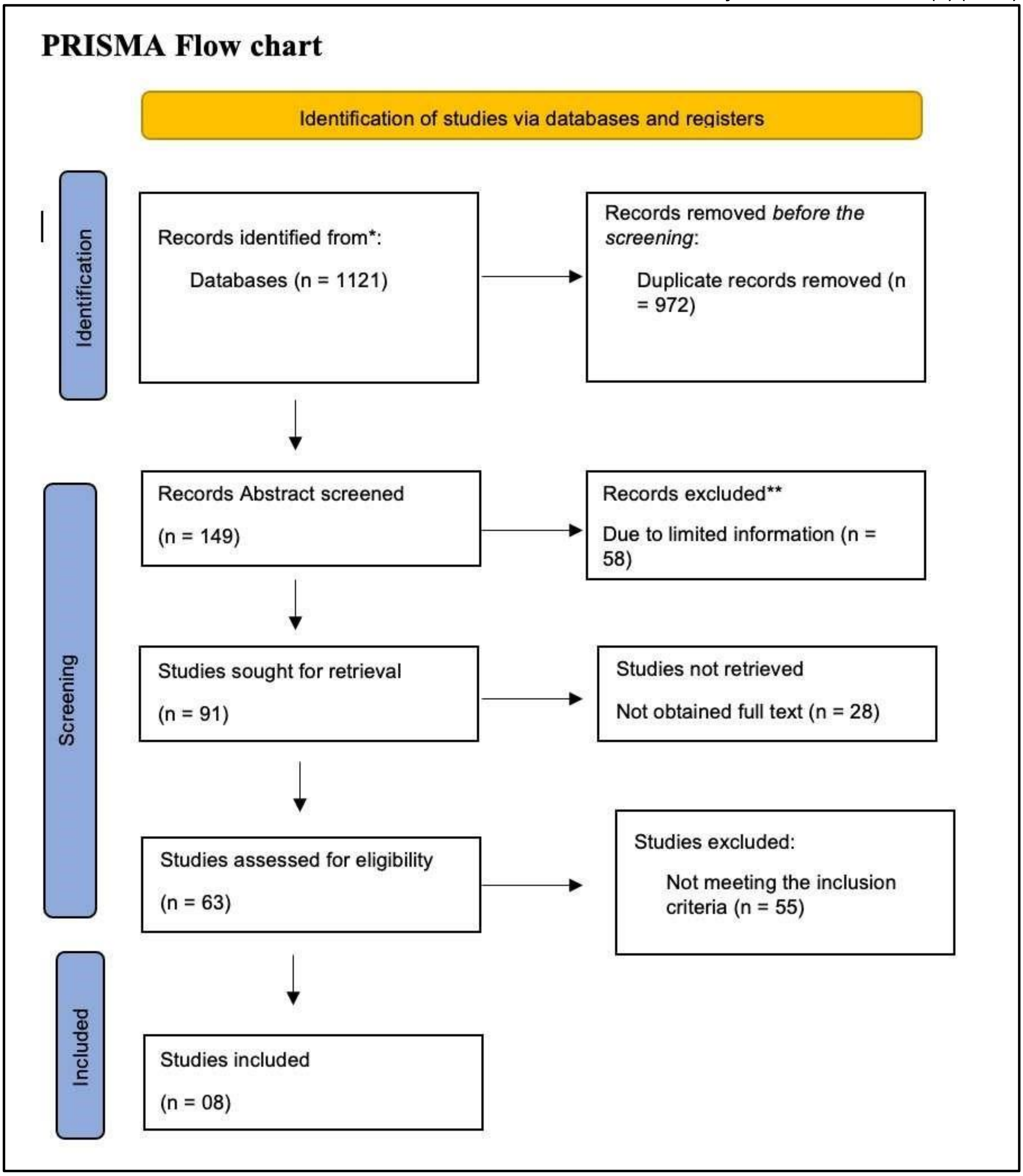

Figure 5: PRISMA flowchart

Table 1: Summary Table

Reference	Title	Aim	Research Design	Method	Findings	Limitations
[47]	Simulation-based approximate policy iteration for dynamic patient scheduling for radiation therapy	Develop a simulation-based approximate policy iteration for dynamic patient scheduling in radiation therapy.	Quantitative modeling and simulation approach	Markov Decision Process (MDP) with Approximate Dynamic Programming (ADP).	The ADP approach performs better than a myopic heuristic decision rule in scheduling efficiency.	MDP approach struggles with large state spaces, requiring approximation.
[48]	A mathematical programming model for optimizing the staff allocation in radiotherapy under uncertain demand.	Optimize the allocation of radiotherapy technologists under uncertain demand using a stochastic mixed-integer programming model.	Quantitative optimization and simulation-based research design	Stochastic Mixed-Integer Linear Programming (MILP) using real patient data.	Optimized staff allocation increases the percentage of patients meeting waiting time targets by up to 10%.	Limited by data availability from a single institution; generalizability needs further testing.
[49]	A Prediction-Based Approach for Online Dynamic Appointment Scheduling: A Case Study in Radiotherapy Treatment.	Propose a prediction-based approach for online dynamic radiotherapy scheduling.	Quantitative modeling and machine learning-based research design	Regression-based model trained on patient arrival patterns and scheduling decisions.	Prediction-based scheduling reduces overdue treatments for emergency patients and optimizes resource use.	Dependent on training data quality; does not account for unexpected large influxes of patients.
[50]	Simulation-based optimization of radiotherapy: Agent-based modeling and reinforcement learning. Mathematics and Computers in Simulation	Develop an agent-based model and reinforcement learning optimization for radiotherapy dose calculation.	Computational modeling and optimization research design	Agent-based simulation of tumor growth combined with Q-learning reinforcement learning.	Optimized fractionation schedules improve tumor treatment effectiveness with minimal side effects.	Model assumes perfect knowledge of tumor growth parameters; real-world variability may impact results.
[51]	Utilizing online stochastic optimization on scheduling of intensity-modulate radiotherapy therapy (IMRT).	Utilize online stochastic optimization for scheduling intensity-modulated radiation therapy (IMRT).	Quantitative optimization-based research design	Mathematical modeling with online stochastic optimization and genetic algorithms.	The scheduling model improves patient flow and reduces waiting times based on real clinical data.	Computational complexity of the genetic algorithm may limit real-time application.
[52]	Strategic level proton therapy	Develop a Markov	Quantitative modeling and	Markov Decision	Optimal patient	Stochastic arrival

	patient admission planning: a Markov decision process modeling approach.	decision process model for strategic proton therapy patient admission planning.	optimization-based research design	Process (MDP) with an aggregated model for handling stochastic patient arrivals.	admission policies balance treatment session allocation and adherence to mix restrictions.	assumptions may not fully capture real-world variations in patient intake.
[53]	Towards a balanced radiotherapy workflow using practical solutions identified by field studies and simulations.	Propose a prediction-based model for online dynamic radiotherapy scheduling with interpretability using SHAP values.	Mixed-methods research design	Regression-based predictive modeling with SHAP values for interpretability.	Prediction-based approach outperforms flat-reservation policies in preventing overdue treatments.	Model does not explicitly handle rare, extreme surge cases in patient arrivals.
[54]	Data-Driven Markov Decision Process Approximations for Personalized Hypertension Treatment Planning.	Analyze radiotherapy workflow and develop scheduling tools for resource optimization.	Quantitative modeling and validation-based research design	Survey, data extraction from oncology information system (ARIA), and simulation modeling.	Custom scheduling tools help distribute workload, and simulations aid in resource allocation planning.	Tool evaluation was limited to Swedish RT departments; broader applicability is uncertain.

Results

Radiotherapy scheduling is critical in the efficient treatment of cancer patients. Due to increasing cancer incidence, the demand for radiotherapy services continues to rise, requiring optimised scheduling approaches that maximise resource utilisation and minimise patient waiting times. This thematic analysis synthesises findings from key studies to understand the different strategies used in radiotherapy scheduling, focusing on themes such as optimisation techniques, patient flow management, and predictive scheduling models.

Optimisation Techniques in Radiotherapy Scheduling

Optimisation models are fundamental for enhancing the scheduling of radiotherapy sessions in a manner that improves the treatment of patients.

Stochastic Models Markov Decision Processes (MDP) and Approximate Dynamic Programming (ADP)

MDPs are a mathematical framework of sequential decision-making under uncertainty, which makes them the perfect choice for radiotherapy scheduling. These models specify state, action, transition probability, and reward to optimise patient flow better. ADP techniques improve MDPs by obtaining value function approximations, reducing computational complexity, and supporting real-time decision-making. As studies [50, 55] show, integrating MDPs with ADP leads to improved patient throughput and scheduling efficiency, which results in waiting times that are about 10–20% less than those obtained by heuristic methods. Dynamically adjusting schedules to patients' arrivals and treatment constraints makes MDPs more adaptable than other scheduling models. In addition, ADP can replace deterministic scheduling, which includes consideration of probabilistic variation in demand and resource availability. Though computational demands remain a challenge, improvements in function approximation and policy iteration methods make it possible to deal with these models. Thus, ADP can be used to implement MDPs in radiotherapy departments to create more adaptive scheduling frameworks, resulting in better patient outcomes and resource utilisation.

Stochastic Mixed-Integer Linear Programming (MILP)
Radiotherapy scheduling based on stochastic variables is widely adopted by incorporating stochastic variables as a MILP-based optimisation technique. The stochastic MILP allows for uncertainties about patient arrivals, necessary equipment availability and treatment time. Research [51] shows that a 10% increase in patients meeting the waiting time target is possible using MILP-based approaches. Nevertheless, these models are computationally expensive on a large scale. As often used for complex integer constraints under uncertainty, it increases the solution times and decreases the real-world applicability. To cope with the above issue, researchers attempted to enhance the computational efficiency through decomposition such as Bender's decomposition and column generation. It has also been observed that the computational burden can be reduced through hybrid MILP models combining heuristic methods without impacting the solution's quality. Structural MILP can optimise patient scheduling and resource allocation to minimise treatment adherence and improve operational efficiency for radiotherapy centres.

Genetic Algorithms and Online Stochastic Optimisation
Genetic algorithms (GAs) are evolutionary optimisation methods that iteratively improve the scheduling solutions through mimicry of natural selection. When included in online stochastic optimisation frameworks, GAs adjusts dynamically as resource availability and fluctuating patient demands vary. The studies [54] suggest that GA-based approaches can cut down the machine idle time by up to 15% by designing optimised treatment schedules continuously. GAs has these advantages: they can explore an ample solution space without being trapped in local optima, and therefore, they are suitable for complex scheduling problems with multiple constraints. Furthermore, a scheduling framework based on GA can implement real-time data to schedule dynamically in response to unexpected delays or cancellations. A significant drawback of GAs is that millions of generations need to be computed; thus, they are computationally costly. This, nonetheless, did not prevent hybrid approaches that employ GAs together with heuristic or rule-based scheduling to produce meaningful, practical improvement in radiotherapy workflow efficiency and responsiveness.

System Dynamics Models Macro-Level Workflow Simulation
System dynamics models model radiotherapy departments to simulate the aggregate behaviour, i.e. patient queues, resource constraints, and treatment flows. Differential equations for analysing the effect of system-wide changes on patient throughput are used for these models. Research [31,32] shows that up to 85% improvement in patient throughput is possible if system

dynamics are integrated with strategic interventions. System dynamics models use key variables such as patient arrival rates, staff availability, and treatment session duration to provide insights into bottlenecks that deter efficiency. System dynamics is more appropriate than discrete event simulation, which is interested in the trajectories of individual patients for policy evaluation, as it allows long-term trends. One application of particular importance is testing how wait times would be influenced by a certain degree of increased staffing levels or extended operating hours. Nevertheless, the validity of these models depends on the quality of the input data and assumptions about the system behaviour. Nonetheless, system dynamics offers a valuable method of optimising departmental operations in radiotherapy.

Causal Loop and Stock-Flow Diagrams

Stock-flow models and causal loop diagrams are essential elements of a system dynamics model in the healthcare specialty, as they provide a visual abstraction of how several factors interact in a healthcare system. Feedback mechanisms are shown by CLDs, such as how delayed treatments cause increased patient backlogs and further increased waiting times. Studies of these feedback loops have shown that policymakers can identify and modify them to design targeted interventions to deal with systemic inefficiency. On the contrary, stock-flow diagrams quantitatively model patients' inflow and outflow through different treatment stages. Human resource constraints can be pictured in these diagrams, and a flow can be predicted for the outcome when staffing or the availability of machines is altered. These models show that resource reallocation strategies based on them can effectively be used to reduce operational bottlenecks.

Hybrid and AI-Enhanced Models Predictive Analytics and Reinforcement Learning

Radiotherapy scheduling adopted advancements in machine learning and used predictive analytics and reinforcement learning. Historical patient data is used to forecast demand patterns by predictive analytics, so resource planning in the hospital can be done proactively. Beyond that, reinforcement learning (RL) arranges the scheduling decisions to be continuously improved, using reward-based optimisation via trial and error. Simulation studies are performed in studies [52,53] that show that RL-driven models can reduce overdue treatments by 20–30%. RL is the key advantage because it can adapt to dynamic environments and is helpful for real-time scheduling adjustments. Expanding on transparency, additional explain ability tools such as SHAP values are embedded to ensure openness, stemming from the black box problems of AI models. However, RL has great potential but lacks scalability regarding computational requirements and requires a lot of training data. However, with one of these barriers, AI-enhanced scheduling frameworks are progressively being applied in radiotherapy management.

Quantitative Comparisons

Difference scheduling models are analysed comparatively, and some advantages of hybrid approaches that combine some elements of stochastic modelling, system dynamics, and AIembodied design decision-making are discussed. The literature reviews show that the hybrid models outperform the single method models by combining the detailed patient-level insights from the stochastic model and the macro-level policy adjustments from the system dynamics. In the context of a patient scheduling problem, for example, on an individual patient scheduling level and system-wide workflow optimisation, agent-based modelling and reinforcement

learning can be used. However, such hybrid frameworks have shown impressive reductions in patient waits and increases in resource utilisation. On the one hand, stochastic models consider uncertainty uncertain but do not provide insight into long-term impacts.
On the other hand, system dynamics addresses impacts in the long term but lacks precision for uncertainty handling. With AI-enhanced methods, scheduling systems are even more responsive to real-time fluctuations. As such, future research is expected to aim at integrating these models further and, in doing so, achieving a seamless combination of predictive, prescriptive, and adaptive decision-support tools in radiotherapy management.
These observations demonstrate the challenges encountered in trying to enhance operational efficiency while maintaining the relativity of advanced scheduling systems to a more practical level in radiotherapy (see table 1: Extraction table).

Predictive Scheduling Models and Machine Learning Predictive Analytics and Reinforcement Learning
Recent research [40,41] integrates machine learning and reinforcement learning into scheduling systems. In simulation studies, these hybrid models have demonstrated reductions in overdue treatments by 20–30%. Explainability tools like SHAP values have been incorporated to improve model transparency. One study showed the effectiveness of machine learning-enabled scheduling in losing pending treatments for emergency patients without compromising the routine patient's waiting period. Incorporating Shapley Additive Explanation (SHAP) values commendably within the scheduling process was able to justify significant SHAP decision steps' importance, thus improving the scheduling transparency considerably [40]. Such openness is imperative as stakeholders in the clinical setup need to understand the basis against which a particular decision about the schedule should be made. In addition, models of real-time changes in radiotherapy scheduling were enhanced by supporting machine learning-powered prediction models. These models changed the scheduling policies automatically based on patient flow volume and available resources, resulting in better management of overdue treatments and optimal capacity utilisation. This new model did outperform the traditional flat-reservation policies, which poorly met patient demand in tandem with available resources. A significant limitation, however, is that it could not incorporate some rare cases of surge attendance where patients attended more than the advanced scheduled appointments, reducing planning efficiency [40]. This evidence indicates the prospects for using predictive analytics in radiotherapy scheduling while emphasising the additional modifications needed to deal with practical complexities.

Quantitative Comparisons
A literature synthesis indicates that hybrid models can outperform single-method approaches by combining the detailed patient-level insights of stochastic models with the macro-level adjustments of system dynamics. For instance, agent-based models combined with Q-learning [41] provided improved dose fractionation schedules that align with clinical guidelines while adapting to real-time changes. The model reflected the dynamic nature of a growing tumour, including the fractionation schedule that maximally destroyed the tumour and minimised damage to healthy tissue. The model and treatment planning that used reinforcement learning in battle strategy proved to be more accurate in the adjustment of radiotherapy doses for the tumour. The primary drawback, however, was the theoretical assumption that parameters

control tumour growth completely. Indeed, there is always some uncertainty in clinical practice. The heterogeneity in tumour response and other patients' factors makes it extremely complex to expect a purely deterministic approach [41].

Patient Flow Management and Resource Allocation

Adaptation of adequate patient flow ensures minimal delays and maximum use of the radiotherapy equipment. Several optimisation frameworks have been provided to improve the scheduling and allocation of resources. One such model is an aggregated Markov Decision Process (MDP) framework, which focuses on strategic proton therapy patient admission planning. Given the strict patient mix constraint, this model was created to evaluate the effectiveness of admission policies in treatment session allocation. The authors showed that scheduling efficiency was greatly enhanced by the modified admission policies that rationally allocated patients to a treatment facility and resources [43]. However, the model emphasised resource allocation and patient scheduling efficiency. Still, a major restraint that could impact actual practice was the patient arrival patterns, which were quite complex.

In another study, radiotherapy workflow optimisation in Swedish departments was focused upon, specifically concerning the scheduling and the usage of simulations. The results underscored the need for innovations in developing scheduling software and managing workflow disruptions from frequent interruptions. Using the analysis of scheduling distortions, the study proposed an innovative method for improving patient flow, which comprises starting preparatory radiotherapy activities one to two weeks before the actual phase of treatment. The strategy was intended to reduce workflow interruptions and improve operational efficiency in radiotherapy departments [45]. Although these results provide important considerations concerning the planning of the scheduling mechanisms, the most significant concern regarding this category of studies is that they have been concentrated only within the context of Swedish radiotherapy departments. That singular focus is problematic because it challenges the applicability of the recommendations to other healthcare systems that operate in constricted parameters and possess different patient flow patterns. These studies have also pointed out the gaps in the modern-day planning of radiotherapy and coping with the challenges of high patient volumes that force implementation delays. On the other hand, they highlight the challenges brought about by actual practice, especially those dealing with complicated patterns of patient admissions and the application of varying healthcare systems.

Discussion

The study's findings reveal important themes regarding optimisation techniques, patient flow management, and predictive modelling in radiotherapy schedules. Scheduling using MDP and ADP has worked well but has shortcomings. The MDP models solve approximations, which could, in turn, lead to inaccuracies [55]. Many studies have addressed this problem of computational feasibility versus optimality in scheduling models [56]. It has been noted that the advantages of modelling stochastic techniques using genetic algorithms approaches require many computational resources. It has also been pointed out that the adapting nature of healthcare settings has tremendous power that is thwarted due to constraints like insufficient data and tedious, time-consuming processing [57]. It can be inferred that the unexplored area, which inadequately addresses real-world constraints vis a vis stochastic optimisation in clinical practice, is bound to face issues.

Regarding MDP usage in patient flow management and its admission planning, it is notably relevant to proton therapy [58]. It is clear, however, that other more adaptive methods, like reinforcement learning, could be helpful. Claims about the capabilities of Q-learning concerning radiotherapy dose fractionation optimisation corroborate this. Unlike traditional stochastic models, Reinforcement learning permits continuous changes to real-time scheduling algorithms that are appropriate for a given level of patient care, which makes them ideal for most functioning hospitals [59]. As has been the case with other machine learning applications in medicine, reinforcement learning can enable the design of more responsive and non-linear patient scheduling systems.

Real-world workflow problems provide helpful information, especially regarding staff scheduling during rush hours. It also suggests that human elements should be incorporated into scheduling models [60]. Incorporating qualitative data from healthcare professionals makes optimising workflows more effective and applicable to real-world scenarios. Unlike machines, scheduling staff entails additional considerations such as fatigue and understanding the morale of the staff, some of the most taken-for-granted factors in mathematical optimisation models [61]. Furthermore, adding human components to scheduling enhances overall effectiveness and makes adherence to scheduling guidelines more likely, as pointed out by studies focusing on the hospital workforce. In terms of scheduling radiotherapy, the introduction of predictive scheduling models is a new development. These regression-based models are applied to historical datasets to create schedules that can dynamically respond to changes. Unfortunately, machine learning models are prone to problems with data and quality control; they struggle with high-impact rare events like surges of patient arrivals [62]. This issue is highly publicised in the machine-learning world. The phenomenon where a model based on complete historical data has been trained on outliers tends to create desperate problems for the model [63]. Hybrid models, with machine learning-based components along with rule-based scheduling techniques, can be used to mitigate these issues.

The literature indicates the most promising strategy for radiotherapy scheduling is the use of hybrid approaches that combine optimisation techniques with predictive modelling. For example, MDP using reinforcement learning or stochastic models combined with machine learning may provide stronger and more flexible scheduling systems [64]. Using these methods in conjunction will benefit both optimisation and predictive modelling because optimisation models can aid in structuring decision-making. In contrast, machine learning models provide flexibility and the ability to learn and adapt in real-time. Hybrid models are handy when addressing uncertainty and variability in patient demand. Traditional optimisation models like MILP and MDP come with set constraints and assumptions that are rarely actual in a dynamic hospital environment [65]. However, machine learning models, especially reinforcement and deep learning, are more easily tailored to changes in patient demand, as seen in AI healthcare decision-making systems.

Nonetheless, some barriers hinder the effective implementation of hybrid models. One of the primary issues is the strain on computing resources posed by the amalgamation of multiple sophisticated approaches. The peripheral requirements of reinforcement learning on big data sets are substantial, and therefore, implementation within health institutions, especially under resourced ones, may not be possible. Besides, these models are too complex to be easily interpretable. Several machine learning algorithms that work as deep learning-based reinforcement learning suffer from a lack of transparency. This can pose a problem for

healthcare professionals in understanding the reasons for specific scheduling choices. Therefore, there has to be a focus on explainable AI methods so that healthcare professionals can authenticate the recommendations and check the logic behind the suggestions of AI-based scheduling.
Besides these, hybrid models are needed to maximise the efficiency of radiotherapy scheduling. Further work should aim to improve the clinical applicability of such models with improved efficiency, easier understanding, and low computational resources. Moreover, randomised trials coupled with pilot studies should take the lead step towards the clinical applicability of the model. Additionally, incorporating contemporary data from hospitals, electronic health records, and artificial intelligence can make this model more versatile and usable in various clinical situations.

Clinical Applications

Improvement of radiotherapy schedules can start with the single-facility level, where the capacity planning, inflow of patients, and machine time are handled locally. Theoretical models are effective when applied in a simulated context; however, real-world examples are more persuasive [66]. One good example is the case of a supervised oncology hospital in Canada, where a queuing-based stochastic model into a real-time scheduling dashboard achieved quantifiable benefits [67]. The present case demonstrates how intelligent scheduling can be transformative even in an individual institution by applying historical data and using adaptive algorithms.
Conversely, scheduling of multi-facility coordination of radiotherapy adds a different aspect of complexity. It requires harmonisation of systems different from hospitals, diverse kinds of equipment, clinical practice, and patient demographics. Regional optimisation can be illustrated using a real-life example in the Netherlands, which has a network of five radiotherapy centres [68]. In this case, attempts to optimise capacity and mitigate unequal access outcomes saw the implementation of an integrated scheduling scheme aimed at rerouting patients according to the availability of machines and travel limitations. Nonetheless, some barriers to implementation were experienced despite the region-wide success in minimizing the treatment backlog by 12%. Data integration barriers were foremost because all facilities had distinct information systems, and HL7/FHIR interoperability standards were the crucial but not the only prerequisites without significant IT coordination. There was also the arising of complexities in governance since central coordination had to harmonise standardisation and autonomy at each facility. Finally, patient preferences, especially treatment in a facility near home, tended to conflict with optimal recommendations system-wide [69]. These aspects highlight the significance of strong governing structures and patient-related modification of policies in scaling the optimisation strategies.

Emerging Trends

Predictive analytics represents one of the most emerging fields regarding radiotherapy scheduling. The recent development includes modelling patient no-shows to help schedule inefficiency and resource underutilisation, a significant problem. Elements of feature selection in one multicenter study were distance home facility, past no-show experience, appointment lead, and socioeconomic characteristics. The very last model was built with gradient boosting algorithms, which is much better than the logistic regression baseline; the results show that not only is it beneficial to include detailed patient data in the design for a model, but sophisticated machine learning is essential in forecasting operations.

Irrespective of these developments, several research gaps still need more attention. First, there are no common disruption scenarios that can be applied in various studies to compare the resilience of scheduling algorithms. Second, the current simulation environment tends to be too ideal, leading to not simulating real-life complexity with variable patients, machine downtime, and manual overrides [70]. Third, clinicians who access schedules through dedicated user interface apparatus often face a lack of balance and web design, which will create friction between the model recommendations and clinical uptake. Adaptive user interfaces that devices communicate on schedule changes and their underlying rationale should be developed as research. Lastly, future research must identify multi-dimensional assessment standards beyond accuracy and speed to balance computational efficiency, clinical interpretability, and user satisfaction.

Implementation Considerations

Scheduling optimisation models need a sound technical infrastructure to be effectively implemented. These range from retrospective data, ideally 12 months (or more) of historical appointment data for training and validation, to real-time data streams updated every 5 minutes to allow responsive scheduling changes. It is also essential that it can be seamlessly integrated with the existing hospital systems, which are usually 3 to 5 clinical systems, including EHR, oncology management, imaging, and scheduling systems, among others. Such systems must have HL7 or FHIR interfaces so rollout is not disruptive.

Nevertheless, technical capacity is insufficient to ensure that successive organisational risk factors, especially staff resistance, are addressed. The causes of resistance can be seen as the feeling of loss of control, apprehensiveness towards new technology, or uncertainty about the transparency of the model. An effectively used five-strategy approach is: (1) including frontline staff in co-design, (2) providing appropriate training, (3) retaining override authority, (4) piloting then deploying afterwards, (5) and of performance impact.

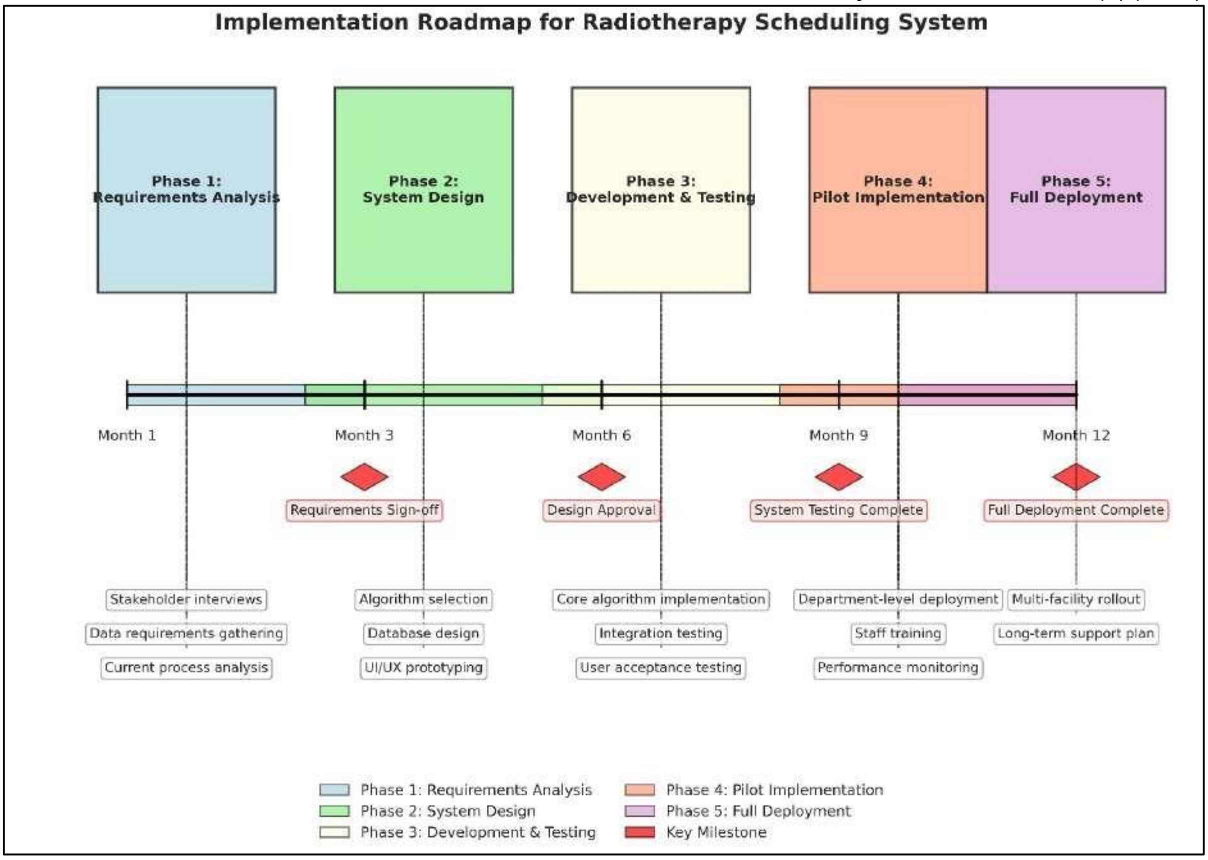

Figure 6: Implementation Plan Roadmap

Conclusion

Effective outcomes in the treatment of cancer and resource utilization require the development of new and efficient solutions in radiotherapy scheduling. Scheduling inefficiencies tend to have an adverse impact, and even a slight delay in treatment results in a poor prognosis, especially in aggressive cancers. Integrating Markov chains, Monte Carlo simulations, and queuing theory into patient flow management has significantly decreased machine idle time and improved overall resource utilization. These methods help healthcare institutions enhance appointment allocations and reduce scheduling bottlenecks. There is also increased flexibility with system dynamic models, which enable health service managers to implement adaptive frameworks for scheduling that enhance staff and equipment deployment while remaining flexible on treatment time. These models allow healthcare providers to appropriately balance the demand versus resource availability while ensuring uninterrupted treatment sessions. Artificial intelligence and machine learning enhance real-time adaptability, which is also something to consider for future improvements. Using Artificial Intelligence, one can predict useful information with reasonable accuracy that enhances an organization's decision. For instance, forecasting the arrival of patients, anticipating possible breakdowns of equipment, or estimating the best-fit appointments based on the available data can be done. Further studies should be directed towards using EHRs with active surveillance for more accurate scheduling. The technological approach to effectively solving scheduling problems in radiotherapy showed that result-oriented and time-effective multitasking is realistic and attainable without infringing on patients' rights or equal access to essential treatment. Such achievement can potentially increase the efficiency of radiotherapy services and eliminate the problem of treatment procrastination and shortage of resources from these healthcare systems.

Recommendations for Future Research and Practice Integration with EHR and Real-Time Monitoring

To make real-time data-driven decisions in future scheduling models, there should be seamless integration with Electronic Health Records (EHR). Live patient updates, including change of appointment, treatment progress and unexpected delays, can be incorporated by scheduling algorithms to improve efficiency [13,18] optimally. This integration would help automate rescheduling and redisclosure of missed and delayed appointments based on resource availability. This could also make such systems available to monitor real-time inefficiencies, track key performance metrics, and give actionable insights to healthcare providers [17]. Such systems require substantial improvement in the data interoperability standards between EHR platforms and optimization models, as well as robust security measures to facilitate communication between the EHR platforms and the optimization models.

Hybrid Model Implementation

It is a promising avenue towards improving radiotherapy scheduling based on the combination of stochastic optimization, system dynamics, and an AI-driven model. Stochastic models can deliver precision in terms of the treatment of uncertainties, system dynamics allow the treatment of large-scale characteristics at the macro level, and AI improves real-time adaptability. These strengths can be combined in a hybrid way, and their weaknesses can be offsite so that more robust and flexible scheduling systems can be developed [17,20]. Future work should focus on the development of frameworks that marry these methodologies well to be scalable and computationally feasible. Hybrid models should also be piloted in clinical settings to validate their performance and improve patient care while improving operational efficiency [14,16].

Focus on Unplanned Gaps

Unintended gaps can disrupt radiotherapy workflows, such as room availability, equipment and staffing schedules, and lack of continuity in patients' work schedules and no-shows or cancellations. Future research should be more focused on developing predictive algorithms to predict such gaps and reassign resources to balance disruptions [18, 19]. Anomalies in unplanned gaps can be detected using machine learning techniques such as anomaly detection and reinforcement learning. Thus, existing issues can be responsive to prevent these before they occur. Also, real-time decision support tools would be required to enable them to efficiently reallocate patients or re-distribute workload [10, 28]. To devise these algorithms in practice, they need to be validated through simulation studies and clinical trials.

Broader Clinical Validation

It has been shown that various scheduling models have performed very well in simulation studies, but their actual deployment across a wide range of healthcare settings has not been well tested. Future research should be expanded to include the conduct of multicenter randomized controlled trials (RCTs) to assess a model based on different patient demographics, hospital infrastructure, and workflow constraints [15, 19]. These scheduling approaches could be rigorously studied in such trials using empirical evidence on the feasibility, scalability, and clinical benefits of such an approach [17, 19]. Qualitative studies are further required to assess the degree to which healthcare providers will adopt the models and that the models are intuitive and practical. However, it will be necessary to broaden clinical validation to integrate these models into standard radiotherapy practice.

Future research should focus on integrating Electronic Health Records (EHR) with real-time monitoring systems to enable adaptive and data-driven radiotherapy scheduling. Developing hybrid models combining AI, stochastic optimization, and system dynamics can enhance flexibility and predictive accuracy. Emphasis should be placed on forecasting unplanned gaps using machine learning to optimize resource reallocation. Pilot testing these innovations in clinical settings is crucial to validate their effectiveness. Additionally, broader clinical validation through multi-centre randomized controlled trials is essential to ensure feasibility, scalability, and user acceptance. Such advancements can significantly enhance patient care, operational efficiency, and equitable access to radiotherapy services.

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