FACULTY OF ENGINEERING
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The impact of artificial intelligence on the cost of radiotherapy in low- and middle-income countries

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As I conclude this thesis, I also close the chapter on my academic journey. Reaching this milestone has required time management, determination, and disciplined focus. Along the way, I have gained a wealth of knowledge that I deeply value. This accomplishment, however, would not have been possible without the guidance, encouragement, and support of many individuals. I am sincerely grateful to all who contributed to this process. It has been a privilege to explore and contribute to research at the intersection of radiotherapy, artificial intelligence, and global health, an area of immense significance and personal interest.

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Explanation regarding the master's thesis and the oral presentation

This master's dissertation is part of an exam. Any comments formulated by the assessment committee during the oral presentation of the master's dissertation are not included in this text.

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Abstract

This master's thesis explores how artificial intelligence (AI) can help address economic and operational barriers to radiotherapy in low and middle income countries (LMICs), where access is limited despite a rising cancer burden. A major obstacle in these regions is the shortage of trained professionals and the high cost of treatment planning and delivery.

The study evaluates whether the Radiotherapy Planning Assistant (RPA), an AI based tool, can improve efficiency and reduce costs in LMIC radiotherapy departments. Data from four centres in the ARCHERY study,covering cervical, head and neck, and prostate cancers, were analysed using the ESTRO HERO Time Driven Activity Based Costing (TDABC) model. Simulations modelled planning time reductions of 70 percent, 80 percent, and 90 percent for eligible tumour types.

Baseline results showed equipment as the dominant cost driver, limiting overall cost reductions. However, time savings from AI integration improved treatment planning system availability and reduced staff workload. These gains suggest enhanced efficiency and capacity, especially in high volume settings. While AI may not yield large financial savings alone, it alleviates key bottlenecks and supports workforce optimisation, provided infrastructure and system capacity are strengthened.

Keywords: EBRT, artificial intelligence, LMICs, Time-Driven Activity-Based Costing, ARCHERY study

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***Abstract*—This study evaluates the economic and operational impact of artificial intelligence (AI)-based radiotherapy (RT) planning in low- and middle-income countries (LMICs), using the ESTRO-HERO Time-Driven Activity-Based Costing (TDABC) model. Drawing on baseline data from four LMIC centres in the ARCHERY study, three simulation scenarios were modelled to assess how the Radiotherapy Planning Assistant (RPA) could alter costs, staffing needs, and workflow efficiency. Results show that while AI-assisted planning significantly reduced planning-related personnel time and treatment planning system (TPS) demand, particularly under full departmental deployment, the overall spending-based departmental costs remained unchanged due to the dominance of fixed infrastructure and staffing expenses. Usage-based costs declined modestly (up to 3.6%) in partial implementation and more in full-scope scenarios, particularly in centres with existing planning bottlenecks. These findings highlight the context-dependence of AI's value: automation offers meaningful efficiency and resource relief, but alone is insufficient to overcome broader system constraints such as treatment delivery capacity. AI tools like the RPA should be strategically deployed in LMICs to target local resource gaps, support internal task reallocation, and enhance planning workflow resilience.**

***Index Terms*—EBRT, artificial intelligence, LMICs, Time-Driven Activity-Based Costing, ARCHERY study**

I. Introduction

Radiotherapy (RT) plays a crucial role in global cancer management, recommended as an essential component of care for approximately half of all cancer patients [1]. However, substantial gaps in RT access exist, particularly in low- and middle-income countries (LMICs), where only around 10% to 40% of patients have access, compared to nearly universal access in high-income countries [2] [3]. With cancer incidence in LMICs projected to increase dramatically by up to 70% by 2030 [4],these disparities underscore an urgent need to expand RT services and infrastructure.

One of the main barriers to providing effective RT in LMICs is the severe shortage of qualified healthcare professionals, alongside high operational and equipment costs [5] [6]. Artificial intelligence (AI) has recently been proposed as a means to address these resource challenges, particularly through automation of the highly labor-intensive processes of contouring anatomical structures and generating treatment plans. The Radiotherapy Planning Assistant (RPA), an AI-based software, has shown promise in significantly reducing these planning times while potentially improving consistency and quality [2]. Yet, robust economic evaluations assessing the real-world impact of such AI tools on RT costs and efficiency in LMICs remain limited [7].

This study aims to fill this evidence gap by evaluating the economic and operational impact of implementing AI-based RT planning in LMIC settings. The analysis draws on data from the ARCHERY study, a prospective, multicentre observational study evaluating the clinical quality and economic impact of AI-assisted treatment planning for cervical, head and neck, and prostate cancers in LMICs [2]. Using the Time-Driven Activity-Based Costing (TD-ABC) model developed by the European Society for Radiotherapy and Oncology (ESTRO) as part of its Health Economics in Radiation Oncology (HERO) initiative [8] [9], this thesis quantifies how varying levels of AI-driven time savings affect cost structures and resource utilization across the six participating RT centres. By providing standardized and context-specific cost data, the findings aim to guide sustainable investments in AI-driven innovations to enhance access to high-quality RT in resource-constrained environments.

II. Methods

This study employs simulation-based modelling to assess how integrating AI into RT planning could affect departmental costs and resource use in LMICs. The analysis draws upon 2022 baseline data collected from the six RT centres participating in the ARCHERY study, prior to clinical deployment of the RPA. The reasoning behind this is that, given the ongoing nature of the ARCHERY study, it was not possible to obtain the complete results within the time frame of this thesis.

A. Costing framework

The costing analysis was conducted using the ESTRO-HERO TD-ABC model [8] [10]. This model captures the structure, staffing, and operational costs of RT departments in a standardized manner across three distinct layers: (1) the EBRT-Core layer covering direct patient-related external beam RT activities; (2) the RO-Support layer comprising clinical quality assurance and shared support tasks; and (3) the Beyond-EBRT layer for institutional and administrative overheads.

Activities in the EBRT-Core were defined by tumour site and technique, including steps such as imaging, treatment planning, verification, delivery, and follow-up. For each

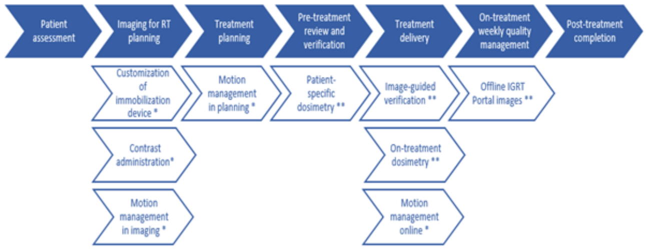

Fig. 1. EBRT-Core care patient-related pathway within the ESTRO-HERO model. Optional steps indicated by asterisks vary based on tumour site, technique, or protocol.

activity, participating centres provided time allocations by professional task group (clinical, planning, physics, etc.), alongside resource inventory, salaries, infrastructure costs, and consumable usage. As illustrated in Figure 1, the EBRT-Core pathway includes both mandatory and optional steps (e.g., image guidance, motion management), the inclusion of which varied by tumour type and protocol.

The cost of each activity was calculated using the TD-ABC method, which involves multiplying the time consumed by each resource by its Cost Capacity Rate (CCR). The CCR is defined as the annualised cost (e.g. salary, depreciation, maintenance) divided by the available clinical minutes, with adjustments made for administrative time and leave. Shared support and institutional costs were allocated to patient courses using a standard 20/80 distribution rule: 20% based on number of courses, 80% on number of fractions delivered [10].

B. Simulation design

To evaluate the effects of AI-assisted planning, baseline ESTRO-HERO models were adapted to allow tumour-type-specific time modifications. The original model structure differentiates activities by treatment technique (e.g., VMAT, 3D-CRT) but not by tumour site, limiting selective analysis. To address this, each technique commonly used for ARCHERY tumour types (cervical, prostate, and head and neck cancers) was duplicated into a custom version (e.g. $VMAT\_archery$). This allowed planning time reductions to be applied only to the subset of patients eligible for AI-based planning.

AI impact was modelled by reducing the time allocated to the “Treatment Planning” and “Motion Management in Planning” activities by 70%, 80%, and 90%, reflecting reported efficiencies in the literature [11]– [15]. These reductions were applied across all relevant task groups. In Simulation 1, these time reductions were modelled without added overhead. Simulation 2 introduced a 10-minute verification step to reflect clinical quality assurance (QA) practices [13] [16]. Simulation 3 extended the 80% time reduction to all tumour types and techniques, representing a hypothetical full-department AI adoption scenario.

This flexible adaptation approach preserved baseline clinical volumes while enabling targeted simulation of AI-driven workflow changes in LMIC RT settings.

C. Cost Analysis

Both spending-based and usage-based cost outputs were analysed. The spending-based approach reflects infrastructure and budget requirements assuming full resource availability, while the usage-based approach isolates actual clinical resource consumption. Comparisons were made between baseline and simulation models in terms of total departmental cost, average cost per EBRT course, and full-time equivalent (FTE) staffing needs by task group.

All monetary values were converted to euros using the European Commission’s official June 2022 InforEuro exchange rate [17], aligning with the midpoint of the baseline reference year. Summary statistics across the six centres included mean percentage change and standard deviation. As the model generates deterministic outputs, no inferential statistical testing was applied.

III. Results

Of the six participating centres, only four completed the ESTRO-HERO TD-ABC model within the time frame of this master thesis. These included the King Hussein Cancer Centre (Jordan), University Malaya Medical Centre (Malaysia), Groote Schuur Hospital (South Africa), and Tata Medical Centre, Kolkata (India). The remaining two centres were excluded from further analysis due to delayed data submission.

A. Baseline Departmental costs

Total annual spending on EBRT varies widely across centres (Table I). Groote Schuur hospital reports the highest annual cost at €6.71 million, followed closely by Tata medical centre, Kolkata (€6.24 million) and University Malaya medical centre (€5.97 million), while King Hussein cancer centre operates on a more modest budget of €3.29 million. Although EBRT pathway activities dominate costs at all centres, their internal composition varies considerably. University Malaya medical centre and King Hussein cancer centre are highly equipment-focused, allocating 70.5% and 88.4% of EBRT costs to equipment, respectively. Groote Schuur hospital stands out as more labour-intensive, with 14.3% of EBRT spending attributed to personnel, while Tata medical centre, Kolkata falls in between at 11.1%. Consumables represent a minor share of overall EBRT costs across all centres, ranging from 0.1% to 3.7%.

B. Simulation 1: AI-assisted planning for ARCHERY tumour types

Simulation 1 explored the theoretical impact of AI integration by simulating an 80% planning time reduction for cervical, prostate, and head and neck cancers. While planning durations themselves are not generalizable to clinical outcomes, the resulting changes in resource allocation and

TABLE I

TOTAL ANNUAL SPENDING-BASED DEPARTMENTAL COSTS BY CENTRE, WITH BREAKDOWN OF EXPENDITURES ACROSS MAJOR COST CATEGORIES (INCL. EBRT, RO SUPPORT AND NON-EBRT COST)

Resource	Grote Schuur hospital	King Hussein cancer centre	Malaya medical centre	Tata medical centre, Kolkata
Total (€)	6,705,830.35 (100%)	3,294,495.58 (100%)	5,974,790.21 (100%)	6,243,337.42 (100%)
EBRT care pathway steps (€)	3,940,800.51 (58.8%)	3,138,870.60 (95.3%)	4,859,698.79 (81.3%)	5,259,421.56 (84.2%)
Equipment (€)	2,912,746.42 (43.4%)	2,911,439.23 (88.4%)	4,212,813.27 (70.5%)	4,511,037.42 (72.3%)
Personnel (€)	957,247.18 (14.3%)	106,724.69 (3.2%)	643,237.41 (10.8%)	692,053.38 (11.1%)
Consumables (€)	70,806.91 (1.1%)	120,706.68 (3.7%)	3,648.11 (0.1%)	56,330.76 (0.9%)
RO Support (€)	1,778,061.14 (26.5%)	113,236.12 (3.4%)	524,869.25 (8.8%)	798,713.27 (12.8%)
Non-EBRT Care (€)	986,968.69 (14.7%)	42,388.85 (1.3%)	590,222.17 (9.9%)	185,202.60 (3.0%)

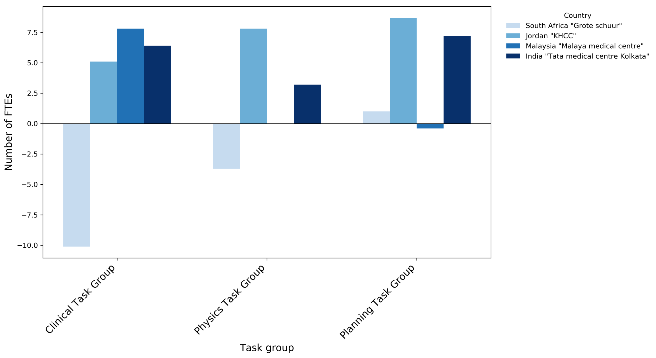

Fig. 2. Simulation 1: Modelled personnel surplus and shortfall by centre, relative to EBRT care pathway demands. Surplus (positive) and need (negative) are expressed in full-time equivalents (FTEs) for clinical, physics, planning, and treatment delivery staff.

departmental cost structure provide meaningful insights into potential efficiency gains.

1) Resource allocation and operational impact: AI-assisted planning resulted in a measurable reduction in staffing requirements across all participating centres, with the most pronounced impact observed in the planning task group. On average, planning-related full-time equivalent (FTE) demand decreased by 0.9 FTEs per centre (SD = 0.4 FTE). Clinical staffing requirements declined by 0.3 FTEs on average (SD = 0.2 FTE), while changes in physics staffing were minimal, with an average reduction of 0.1 FTEs (SD = 0.1 FTE). Figure 2 illustrates the estimated FTE surplus or deficit across major staff groups, based on the available FTEs and the estimated staffing needs derived from time allocations for each step in the EBRT care pathway. While the simulations demonstrate clear efficiency gains from AI integration, these improvements are insufficient to fully resolve existing personnel bottlenecks, particularly in centres already operating below optimal staffing levels.

Treatment planning system's (TPS) availability improved across all centres. At baseline, one centre exceeded its planning system capacity; under Simulation 1, demand fell to within available limits. Overall, average TPS utilization dropped by 0.3 units, alleviating infrastructure pressure and creating latent planning capacity.

Equipment task time allocation also shifted modestly. Planning activities accounted for a smaller share of total equipment time (- 5.9% on average), while treatment delivery (+4.1%) and image-guided localisation (+2.0%) experienced slight increases. These changes reflect downstream rebalancing as planning becomes more efficient.

2) Cost Impact: In Simulation 1, total departmental costs remained unchanged under the spending-based approach, which allocates fixed budgetary resources. However, usage-based costs, which reflect actual resource consumption, declined modestly in all the centres, with an average reduction of - 2.5%. The largest decrease was observed at Tata Medical Centre (- 3.6%). These reductions were primarily driven by decreased demand for planning-related personnel and equipment.

Although the total cost per EBRT course remained stable in the spending-based model, minor shifts occurred within the internal cost distribution. Planning-related shares of both equipment and personnel costs declined by approximately 3–4%, with the largest reallocation observed at TMC, where planning costs were partially absorbed by review and verification activities. Across all centres, task rankings for cost drivers remained stable, indicating that AI integration did not fundamentally alter departmental spending priorities.

Technique-level analysis showed heterogeneous effects. While VMAT consistently yielded cost reductions across centres, 3D-CRT and stereotactic planning sometimes produced higher costs, particularly in centres with limited baseline automation or smaller case volumes. Tumour-specific analysis showed average EBRT course cost reductions of 5.9% across ARCHERY cancers, with the most substantial drop for cervical cancer (- 22% at Tata medical centre, Kolkata). However, some centres, such as King Hussein cancer centre , exhibited slight cost increases across all tumour types, highlighting the influence of local infrastructure and baseline workflows.

Sensitivity analysis confirmed that additional gains beyond the 80% scenario were limited. Differences in total departmental usage-based costs and planning-related cost shares and resource allocation between 70%, 80%, and 90% scenarios were consistently below 2%, indicating diminishing returns with deeper automation. Cost structures at both the technique and tumour-type level remained robust despite variations in assumed efficiency.

C. Simulation 2 and 3: Supplementary Scenarios

Simulation 2 introduced a 10-minute QA check into the planning workflow to simulate clinical verification steps. This addition had no measurable impact on resource allocation or operational efficiency. TPS demand and personnel FTEs remained unchanged across all centres. The cost impact was negligible, with only a minor increase in the unit cost of pretreatment review and verification activities.

In Simulation 3, the planning time reduction was extended to all tumour types across the department. This broader application produced more substantial effects compared to Simulation 1. TPS demand decreased sharply, resolving capacity bottlenecks at all centres. Planning-related equipment and personnel time dropped markedly, with planning falling out of the top three time drivers at most centres. Personnel needs decreased by an average of 2.6 FTEs for planners, with smaller reductions for clinical and physics staff.

Usage-based departmental costs declined by an average of 3.7%, with the largest reduction (–9.8%) observed in the Indian centre. Planning-related costs per course fell by over 40% across techniques, particularly for more complex modalities such as IMRT and VMAT. While total departmental costs under the spending-based model remained constant, internal reallocations showed planning's relative share decreasing across both equipment and personnel budgets.

IV. Discussion

This study assessed the potential impact of AI-based RT planning in four LMIC centres using the ESTRO-HERO TDABC model. Simulation results suggest that while AI tools like the RPA can deliver meaningful efficiency gains, particularly in planning personnel time and TPS utilization, their ability to drive cost savings is limited by the dominance of fixed departmental costs. Most financial and equipment resources in RT are tied up in infrastructure and salaried staff, meaning that even significant time reductions in planning do not translate to overall budgetary savings.

Simulation 1, which modeled partial AI deployment for cervical, prostate, and head and neck cancers, showed moderate resource relief, including average planning FTE reductions of 0.9 per centre, and small usage-based cost declines between 0 and 3.6 percent, but had no impact on total spending. Simulation 2 confirmed that incorporating a QA step into AI workflows is operationally feasible and cost-neutral, reinforcing the importance of clinical validation. Simulation 3 extended AI planning to all tumour types, demonstrating larger resource savings, especially in centres with staff shortages, but again highlighted that system-level impact depends on whether other constraints, such as LINAC shortages, are addressed.

Importantly, the simulations revealed that the value of AI integration is highly context dependent. Centres with high planning burden and adequate infrastructure benefited most, while departments constrained by treatment delivery resources saw minimal systemic improvement. In such settings, AI tools may improve staff flexibility and operational resilience but cannot substitute for investment in core treatment capacity. These findings support a more tailored approach to AI adoption in LMICs: implementation should align with the specific bottlenecks of each centre and be embedded within broader workforce and infrastructure planning.

Taken together, these findings emphasize that AI planning tools offer operational efficiency and workforce relief but are unlikely to transform RT services without parallel investments in treatment infrastructure and institutional flexibility. The value of AI in LMIC RT thus lies in enabling smarter use of existing resources rather than reducing total costs, positioning it as a strategic lever for improving workflow resilience and patient access, rather than as a standalone cost-saving intervention.

V. Conclusion

This study evaluated the potential impact of AI-based RT planning on cost structures and resource utilization in LMICs, using the ESTRO-HERO TD-ABC model and primary data from the ARCHERY study. Simulations of the RPA across selected and comprehensive tumour pathways demonstrated meaningful gains in workflow efficiency, particularly through reductions in treatment planning time and TPS demand. However, the overall financial impact remained modest due to the predominance of fixed equipment and personnel costs, which limit flexibility under current cost structures.

Although automation did not substantially reduce departmental spending, it did allow personnel time to be reallocated and planning bottlenecks to be alleviated. These benefits are particularly relevant in settings with workforce shortages. Yet, increases in patient throughput remain contingent upon available capacity across the entire RT workflow, highlighting the importance of considering AI implementation within the broader system context.

This work also underscores the methodological challenges of performing standardized economic evaluations in RT, where variations in local infrastructure, data quality, and modelling assumptions complicate generalization. Future research should extend these findings into dynamic models that incorporate clinical outcomes, system-level constraints, and real-world implementation data to more comprehensively assess the value of AI-driven planning in LMICs.

VI. Limitations and future work

While the ESTRO-HERO TD-ABC model is well-established for evaluating RT services, it was not originally designed to assess highly specific innovations like AI-assisted planning. Its general-purpose structure limits its ability to capture the nuanced and evolving workflows introduced by such technologies. Moreover, variation in how centres interpret and input data can compromise consistency across sites. For example, differing definitions of TPS capacity or whether planning time reflects active staff involvement versus passive software processing, as observed in the Malaysian centre, may distort cost and resource estimates. The model also aggregates the planning process, preventing separate analysis of contouring and optimization steps. Finally, implementation costs of AI tools were excluded, and real-world clinical impact was not assessed. Future work should incorporate real-life RPA performance data from the ongoing ARCHERY study, expand to include lower-income countries, evaluate implementation barriers, and link cost dynamics to clinical outcomes. Establishing standardized costing practices across LMIC contexts will also strengthen the comparability and utility of such economic evaluations.

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List of Acronyms

3D-CRT three-dimensional conformal radiation therapy.

ABC Activity-Based Costing.

AI Artificial intelligence.

CCR Capacity Cost Rate.

CNN Convolutional Neural Networks.

CT Computed Tomography.

CTV Clinical Target Volume.

DL Deep Learning.

DVH Dose-Volume Histogram.

EBRT External Beam Radiotherapy.

ESTRO European Society for Radiotherapy and Oncology.

FTE Full-time equivalent.

GAN Generative Adversarial Networks.

GTV Gross Tumour Volume.

HERO Health Economics in Radiation Oncology.

IAEA International Atomic Energy Agency.

IGRT Image-Guided Radiotherapy.

IMRT Intensity-Modulated Radiotherapy.

LINAC Linear accelerator.

LMIC Low- and Middle-income country.

MC Multileaf collimator.

MIC Middle-income country.

MRI Magnetic Resonance Imaging.

OAR Organ at risk.

PET Positron Emission Tomography.

PTV Planning Target Volume.

QA Quality Assurance.

RPA Radiotherapy Planning Assistant.

SBRT Stereotactic Body Radiation Therapy.

TDABC Time-Driven Activity-Based costing.

TPS Treatment Planning System.

VMAT Volumetric Modulated Arc Therapy.

1

Introduction

1.1 Problem statement

Radiotherapy (RT) is of crucial importance in the global management of cancer, with its use being recommended for approximately half of all cancer patients at some point during their treatment (Delaney and Barton [2015]). Nevertheless, access remains extremely restricted in low- and middle-income countries (LMICs), which bear a disproportionate share of the global cancer burden(SAMIEI et al. [2013]). Projections indicate a 70% increase in cancer cases by 2030, driven by factors such as increased life expectancy, rapid urbanisation, and changing lifestyle patterns (Pramesh et al. [2022]). This has the potential to place substantial health, social, and economic pressures on LMICs. These countries often grapple with inadequate healthcare infrastructure and constrained resources, which further complicates the management of rising cancer incidence (Grover et al. [2015]).

A significant barrier to enhancing cancer care in LMICs is the severe shortage of RT services and resources. In low-income countries,only approximately 10% of cancer patients have access to RT, compared to around 40% in middle-income countries (Aggarwal et al. [2023]).The existence of this gap can be attributed to scarcity of suitable infrastructure, poorly maintained and outdated equipment, limited government funding, and severe shortages in skilled healthcare professionals(Anakwenze et al. [2017]).These workforce gaps are particularly difficult to address due to the specialized expertise and lengthy training required. Inadequate RT capacity results in long waiting times, delayed treatment initiation, accelerated disease progression, and increased cancer morbidity and mortality(Hope-Johnson et al. [2024].Economic barriers, such as the high cost of RT and limited health insurance coverage, further restrict access, often pushing families into financial hardship (Aggarwal et al. [2023],Anakwenze et al. [2017].

In addition to resource limitations, a lack of robust economic evaluations and comprehensive cost analyses of RT in LMICs is notable. Detailed cost data are essential for guiding policy and resource allocation, particularly in settings with constrained budgets. However, existing studies often fall short. They tend to be fragmented and methodologically inconsistent, and are frequently based on reimbursement rates rather than actual resource use (Defourny et al. [2016], Van Dyk et al. [2017]). Consequently, their value in decision-making, resource allocation and investment planning is limited.

Given these challenges, artificial intelligence (AI) offers a promising way to improve efficiency and address resource gaps in RT services (Aggarwal et al. [2023]). Tools such as automated treatment planning software can help mitigate workforce shortages, reduce planning time, and minimise human error. By improving consistency and optimising resource use, AI has the potential to expand access and enhance the quality of RT in resource-limited settings (Ramiah and Mmereki [2024]).

While AI-based tools offer potential solutions to workforce and efficiency challenges in RT, there is limited evidence evaluating their economic impact in LMIC settings (Vithlani et al. [2023]). In particular, few studies have assessed how such technologies affect costs, resource use, and overall affordability of care. This master's thesis aims to assess the potential impact of AI for treatment planning on RT costs and resource efficiency in LMICs. Generating robust, standardised cost data is essential to inform policy decisions and support sustainable investments in RT infrastructure. Understanding the economic value of AI tools will help guide their integration into health systems and support efforts to improve access to high-quality cancer care in resource-limited environments.

1.2 Purpose of the study

RT constitutes a critical component of cancer treatment, yet its delivery in LMICs remains constrained by limited infrastructure, high equipment costs, and chronic shortages of trained personnel. The potential of AI-driven planning tools to automate time-intensive tasks such as contouring and treatment plan generation has led to increased interest in their ability to mitigate these structural barriers(Shanbhag et al. [2023]). Nevertheless, the economic value and feasibility of such technologies in resource-constrained environments remains limited (Vithlani et al. [2023]).

The objective of this study is to evaluate implications of integrating AI-based RT planning tools in LMICs on the RT cost and the resource utilization. The study utilises data derived from the ARCHERY study, a multi-country, prospective evaluation of automated RT planning for cervical, head and neck, and prostate cancers (Aggarwal et al. [2023]). While the ARCHERY study primarily investigates the quality and feasibility of AI-generated treatment plans, it also includes cost and resource utilisation impact as secondary outcomes. This thesis makes a contribution to the ARCHERY study by focusing specifically on the secondary objective of assessing the economic and operational impact of implementing AI-based planning in LMIC settings.

This study employs simulation-based analysis and applies the the European Society for Radiotherapy and Oncology – Health Economics in Radiation Oncology (ESTRO-HERO) time-driven activity-based costing (TD-ABC) model to compare AI-assisted versus conventional planning workflows. It quantifies time requirements, staff involvement, and associated costs, providing standardised and context-specific data that can inform health system investment decisions. Beyond assessing efficiency gains, the objective is to evaluate the potential of AI to support more scalable and affordable RT delivery in LMICs.

By doing so, this work contributes to the broader goals of the ARCHERY project and aligns with international cancer control strategies, such as those advocated by the IAEA and the Global Taskforce on Radiotherapy for Cancer Control. These strategies call for cost-effective and sustainable innovations that will expand access to quality RT in underserved areas.(Agency [2024]).

2

Theoretical framework

2.1 Radiotherapy

RT remains a cornerstone of contemporary cancer care, playing a vital role in the multidisciplinary management of malignancies on a global scale. It is estimated that approximately 50%- 70% of cancer patients would benefit from RT at some point in their disease course, either with curative intent or palliative, making it a critical component of comprehensive cancer treatment (Agency [2024]).The global burden of cancer is rising, particularly in LMICs, and the need for accessible, effective, and scalable RT services is becoming increasingly urgent (Abdel-Wahab et al. [2021]).

External beam radiotherapy (EBRT) is the most widely used and adaptable RT modality, applied across a broad range of cancer types. It involves the precise delivery of high-energy radiation beams from outside the body to target tumour tissues while sparing surrounding healthy structures. EBRT has undergone a significant technological evolution, progressing from basic two-dimensional techniques to sophisticated modalities such as 3D conformal radiotherapy (3D-CRT), intensity-modulated radiotherapy (IMRT), volumetric modulated arc therapy (VMAT), and stereotactic body radiation therapy (SBRT). These innovations have significantly enhanced treatment accuracy, safety and effectiveness (Vollmering [2021]).

The following sections outline the EBRT workflow and describe the main treatment techniques used in current clinical practice to better understand the operational and technical landscape.

2 Theoretical framework

2.1.1 EBRT workflow

The process of EBRT is multifaceted, involving a coordinated effort by radiation oncologists, medical physicists, dosimetrists, and radiation therapists to ensure safety and efficacy throughout the treatment course.

Following a cancer diagnosis and multidisciplinary team assessment, patients deemed suitable for RT are referred for consultation with a radiation oncologist. During this visit, the oncologist will conduct a comprehensive review of the patient's clinical history, imaging, and pathology to determine the treatment intent, whether it is curative or palliative, and will then prescribe a personalised radiation plan, including the precise dose, target site, and fractionation schedule (Vieira et al. [2019], Misher [2024]). Subsequent to this, patients undergo a simulation session, during which they are positioned with immobilisation devices to ensure reproducibility. A planning computed tomography (CT) scan is then acquired in the treatment position, with MRI or PET imaging being used to refine anatomical detail where necessary (Stiles [2023],Campos [2024]).

The resulting images are then used for contouring, where the gross tumour volume (GTV), clinical target volume (CTV), planning target volume (PTV), and adjacent organs at risk (OARs) are contoured by the radiation oncologist. Utilising this data, a dosimetrist or physicist will develop an optimised treatment plan via inverse planning algorithms that balance tumour coverage with normal tissue sparing.The quality of the plan is evaluated through both dose-volume histograms (DVHs) and visual inspection of the three-dimensional dose distribution. Finally, the plan undergoes rigorous quality assurance (QA) procedures to ensure its safety and deliverability (Delaney et al. [2005],Khan and Gibbons [2014]).

Treatment is delivered in fractions, typically over several weeks. Patients are positioned using the same setup as during the simulation, with alignment verified through image-guided techniques such as cone-beam CT . The actual irradiation time is usually brief, lasting only a few minutes, although the entire session may take between 15 and 30 minutes. Advanced protocols, including hypofractionation and motion management strategies, are implemented where appropriate to enhance precision and reduce treatment burden(Misher [2024],Campos [2024]). Throughout the course, patients are monitored for treatment response and side effects, and upon completion, they enter follow-up to assess therapeutic outcomes and manage any late toxicities (Delaney et al. [2005]).

2.1.2 EBRT techniques

Over the past few decades, EBRT has evolved with the development of increasingly precise and efficient techniques designed to improve dose conformity to the tumour while minimising radiation exposure to surrounding healthy tissues. The most widely used modalities include 3D-CRT, IMRT, VMAT and SBRT.

3D-CRT is considered the cornerstone of modern RT, using CT to create a three-dimensional image of the tumour and surrounding organs (Campos [2024]). This allows clinicians to shape the radiation beam so that it closely matches the target. Multileaf collimators (MLCs) are used to shield normal tissue and guide the beam geometry. Although the beam intensity is uniform, the use of multiple angles allows for improved dose distribution compared to earlier two-dimensional methods. However, 3D-CRT is limited in its ability to shape the dose around irregular or complex tumour volumes (Hall and Wuu [2003]).

IMRT was developed to overcome the dose-shaping limitations of 3D-CRT by allowing modulation of beam intensity across each field, which enables more conformal dose distributions. To illustrate this point, consider the utilisation of concave dose shapes, which have been demonstrated to better spare adjacent organs at risk when tumours are wrapped around or closely situated to them (Knipe et al. [2025b]). This is achieved through dynamic MLC movements and inverse planning algorithms that optimise dose delivery according to clinical objectives. However, the technique is resource-intensive and requires careful QA due to its complexity (Hall and Wuu [2003]).

Building on IMRT, VMAT improves delivery efficiency by administering radiation continuously as the gantry rotates around the patient (Palma et al. [2008]). During this arc-based delivery, the beam shape, dose rate, and gantry speed are dynamically adjusted, achieving comparable or superior conformality in a shorter time than static-field IMRT. VMAT also enhances patient comfort and reduces intra-fraction motion, although it relies on advanced planning software and system capabilities (Hunte et al. [2022]). IMRT and/or VMAT are now considered the standard of care for many complex tumour sites, including the head and neck and pelvis, with a growing number of centres using VMAT as their primary delivery technique (Bollen et al. [2021]).

SBRT, a more recent innovation, delivers ablative radiation doses in a small number of fractions (typically between one and five) but with sub-millimetre accuracy (Massat [2018]). Originally developed for intracranial lesions, its use has expanded to extracranial sites such as the lungs, liver, spine and prostate. SBRT requires rigorous imaging, immobilisation and motion management, often involving respiratory gating or image-guided tracking, in order to maintain treatment precision (Stiles [2023]). Its steep dose gradients and high doses per fraction have demonstrated excellent local control, particularly in early-stage or oligometastatic disease, but require rigorous quality control to ensure safety (Knipe et al. [2025a]).

Taken together, these techniques demonstrate the progression towards increasingly tailored, high-precision RT. The choice of an appropriate modality depends on tumour location, size, movement characteristics and the availability of institutional resources and expertise.

2.2 The use of AI for RT

Recent advances in AI have significantly influenced RT, with applications spanning imaging, contouring, treatment planning, QA , and outcome prediction. AI has demonstrated the potential to improve workflow efficiency, reduce inter-observer variability, and mitigate workforce shortages. This is an especially relevant advantage in low-resource settings (Shan et al. [2024], Landry et al. [2023]). These technologies are particularly valuable in labour-intensive tasks such as treatment planning and OAR contouring, where variability and delays can impact clinical outcomes (Aggarwal et al. [2023]).

One of the earliest and most established uses of AI in RT is auto-contouring. Deep learning (DL) models, particularly convolutional neural networks (CNNs) such as U-Net and its derivatives, have shown strong performance in contouring tumour and OAR volumes. A systematic review by Wang et al. [2024] focusing on CT-based lung cancer contouring reported average Dice similarity scores around 79%, with more recent models demonstrating continued improvement. Auto-contouring tools have also been shown to reduce contouring time by over 50% in specific scenarios, easing clinician workload while maintaining accuracy (Callens et al. [2024], Cui et al. [2023]).

In treatment planning, contouring quality directly influences plan quality. AI-based planning tools, including generative adversarial networks (GANs) and dose prediction models, can generate clinically acceptable dose distributions by learning from historical datasets. This allows for the rapid creation of 3D dose maps within minutes, helping to standardise planning quality and reduce variation between planners (Callens et al. [2024]).

These AI systems have already shown strong clinical performance across various tumour sites. For example, DL-based contouring has been validated in lung and breast cancers, achieving high Dice scores and requiring only minor manual adjustments (Wang et al. [2024]). A study on lung cancer auto-contouring demonstrated that models produced clinically acceptable results, even in anatomically complex cases, reinforcing their practical utility (Moran et al. [2025]).

These developments support the emergence of automated or semi-automated planning workflows, where steps such as contouring, beam configuration, optimisation, and dose calculation are performed by AI systems. While full automation is not yet routine, many workflows have reached Level 2 or 3 automation, as defined by the ESTRO automation taxonomy, indicating increasing reliance on AI tools with clinician oversight still in place (Callens et al. [2024]).

Despite these advances, cautious implementation is essential. Key challenges include automation bias, limited generalisability across populations, and a lack of transparency in how algorithms make decisions. Continued human oversight is critical, particularly in complex or borderline cases. Lessons from other high-risk industries such as aviation may inform strategies to ensure safety, accountability, and sustained clinical trust in AI systems (Callens et al. [2024]).

Although this thesis focuses on AI in planning and contouring, the scope of AI applications in RT is broader. AI contributes to adaptive RT by supporting real-time adjustments based on anatomical changes, improves outcome prediction through radiomics and dosiomics, and enhances safety through automated QA systems. Together, these innovations represent a shift towards more precise, efficient, and personalised RT care (Mastella et al. [2025], Wahid et al. [2024]).

2.3 Time-Driven Activity- Based Costing

2.3.1 General overview of TD-ABC

TD-ABC, as pioneered by Kaplan et al. [2003], is a refinement of Activity-Based Costing (ABC) that aims to improve resource allocation by directly estimating resource consumption based on the time spent on each process step. In contrast to traditional ABC, which relies on surveys and subjective assessments, TD-ABC utilises two key parameters: the Capacity Cost Rate (CCR) and precise time measurements for activities (Kaplan and Porter [2011]).

The CCR is calculated as the cost per minute of providing capacity. This involves the calculation of total annual costs for resources (personnel, space, and equipment) and the subsequent division of this total by the available capacity (minutes per year). This results in a direct measure of resource costs per minute (Kaplan et al. [2014]).

The implementation of TD-ABC follows seven distinct steps: (1) selecting the medical condition or service, (2) defining the entire care delivery cycle, (3) developing detailed process maps, (4) estimating the time spent on each activity, (5) estimating the cost of supplying patient care resources, (6) calculating the capacity cost rate, and (7) summing these figures to obtain the total cost of patient care (Keel et al. [2017]).

2.3.2 TD-ABC in healthcare and RT

Traditional healthcare costing methods often rely on charges or reimbursement rates, which do not accurately reflect actual resource use. TD-ABC provides a more transparent and scalable approach by aligning resource utilisation with clinical workflows, supporting value-based care delivery (Kaplan and Porter [2011], Keel et al. [2017]). The method has been applied across various healthcare domains, from surgery to chronic disease management, and is particularly well-suited to RT due to its structured, multidisciplinary, and resource-intensive nature (Choudhery et al. [2021]).

In the field of RT, TD-ABC can be applied throughout the care cycle, from initial consultation and simulation to planning, delivery, and follow-up. Each activity (e.g. contouring, dose calculation, QA) is assigned a time estimate and matched with CCRs for relevant personnel (e.g. radiation oncologists, physicists, technologists) and equipment. This enables detailed cost analyses that can identify inefficiencies, underused capacity, or workflow bottlenecks (Choudhery et al. [2021]).

For example, Laviana et al. [2016] used TD-ABC to compare CT-guided and MR-guided RT workflows, finding that MR-guided therapy was 18% more expensive under baseline assumptions. However, efficiencies such as eliminating CT simulation or shortening session times could offset this difference, demonstrating how TD-ABC can inform both clinical and financial decision-making.

TD-ABC also aligns with bundled payment and value-based care models, which require cost visibility across the entire care pathway, as opposed to per fraction or visit (Kaplan et al. [2014], Keel et al. [2017]).

2.3.3 ESTRO-HERO model

The HERO project, launched by ESTRO in 2010, aims to address the need for robust, standardised economic data in RT. Given the constrained nature of healthcare budgets and the frequent underfunding of RT despite its cost-effectiveness, HERO seeks to equip the radiation oncology community with tools and evidence to engage with policymakers, funders, and national health authorities (Defourny et al. [2019]).

The initiative spans several dimensions of RT economics, including service provision, accessibility, treatment need versus capacity, and the estimation of RT costs at the national level. These costs are calculated using a tailored TD-ABC model developed to reflect real-world resource use from the perspective of healthcare providers (Defourny et al. [2019], Defourny et al. [2022], Van Dyk et al. [2017]).

The ESTRO-HERO TD-ABC model supports detailed cost analysis across a range of clinical scenarios by linking resource use with tumour site, treatment intent (curative vs. palliative), fractionation, and technique (e.g. 3D-CRT, IMRT, VMAT, SBRT). It also allows for scenario modelling, enabling the assessment of how changes in clinical protocols or technologies (such as hypofractionation or AI-based tools) may affect resource use, staffing, and overall costs (Defourny et al. [2022], Spencer et al. [2021]).

Structurally, the model consists of three layers:

- EBRT-Core: clinical activities for the individual patient, such as imaging, contouring, planning, and treatment delivery, adapted from AAPM workflow recommendations.
- RO-Support: Departmental support functions, including QA and medical physics.
- Beyond-EBRT: chemotherapy, brachytherapy, follow-up consultations and multidisciplinary tumour boards (Defourny et al. [2019],Lievens and Grau [2012].

The model has been applied in various European settings for national resource planning and reimbursement assessments. In Belgium, for example, it supported updates to staffing and equipment guidelines, estimated the cost of implementing advanced technologies such as MR-guided RT, and informed reimbursement revisions, based on expert consensus and real-world data from a reference centre (Defourny et al. [2022]). In Catalonia, Spain, the model was used across 11 public centres to compare costs between curative and palliative treatments, contributing to regional planning efforts (Grau et al. [2018]).

By producing consistent, structured cost data, the ESTRO-HERO model enables economic evaluation, supports resource allocation decisions, and provides a foundation for evidence-based policy development in RT. It is especially relevant for assessing the system-wide impact of emerging technologies such as AI.

2.4 ARCHERY study

This thesis utilises data from the ongoing ARCHERY study (AI-Based Radiotherapy Contouring and Planning Evaluation for Head and Neck, Cervical, and Prostate Cancers in LMICs), a four-year prospective observational project designed to evaluate the quality, efficiency, and economic implications of AI-driven automated RT planning. The study focuses on three prevalent cancer types in LMICs that are commonly managed with RT: cervical, head and neck, and prostate. The study is being conducted across six public-sector cancer hospitals in India, Jordan, Malaysia and South Africa(Aggarwal et al. [2023]).

A central component of the study is the Radiotherapy Planning Assistant (RPA), an AI-based software developed by the University of Texas MD Anderson Cancer Centre. The RPA automates two labour-intensive steps in the RT planning process: the contouring of CTVs and OARs, and the generation of treatment plans, including beam configuration and dose optimisation (Aggarwal et al. [2023]).

The study evaluates whether AI-generated contours and dose distributions meet international quality standards for curative treatment, with emphasis on accuracy, consistency, and adherence to clinical guidelines. It also compares time and staffing requirements between AI-based and conventional manual workflows. These operational data are integrated into a cost-impact analysis using the ESTRO-HERO TD-ABC model to assess the financial and resource implications of AI implementation in LMIC contexts (Aggarwal et al. [2023]).

In addition to its technical assessment, the ARCHERY study aims to inform policy discussions and support the potential adoption of AI-enabled RT tools in resource-constrained settings. By assessing improvements in efficiency, cost, and standardisation, it may contribute to broader efforts to expand access to high-quality cancer care and build research infrastructure in LMICs.

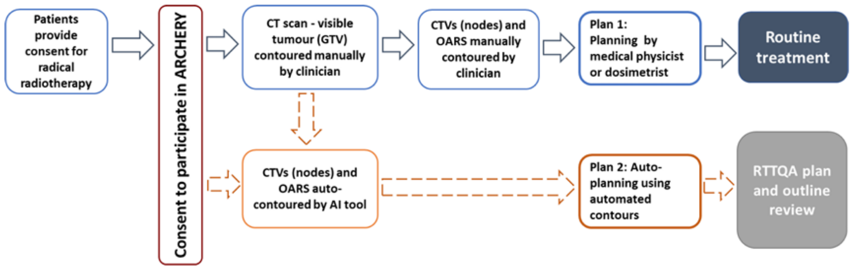


Figure 2.1: ARCHERY treatment plan generation workflow. CTV, clinical target volume; GTV, gross tumour volume; OAR, organs at risk; RTTQA, RT Trials Quality Assurance.

2.4.1 Study workflow

The ARCHERY study employs a structured workflow to evaluate the clinical quality and operational efficiency of AI-assisted RT planning. This encompasses the generation of treatment plans, their quality assessment, and a cost-impact analysis.

Treatment plan generation

For each patient enrolled in the study, RT planning commences with a CT simulation. For head and neck, as well as cervical cancers, the GTV is manually delineated by a clinician. Two parallel plans are then created based on the same scan, as seen in Figure 2.1:

- The first of these is a clinician-guided plan, in which radiation oncologists manually contour clinical CTVs and OARs, and develop the treatment plan according to standard protocols. This plan is then used for the actual patient treatment.
- An alternative plan is generated by the RPA, an AI system that automatically contours CTVs and OARs and generates a treatment plan using predefined algorithms and international clinical guidelines.

In the prostate cancer pathway, there is no GTV to delineate. Instead, the CTV is defined as the prostate gland with or without seminal vesicles and it is outlined either manually by the clinician or automatically by the RPA. As the AI-generated plan is evaluated retrospectively and does not affect patient care, randomisation is not required.

Plan quality evaluation

Plan quality in the ARCHERY study is assessed through a structured two-step validation process, contour evaluation and dosimetric assessment, coordinated by the UK Radiotherapy Trials Quality Assurance group, using protocols from the Global Harmonisation Group.

First, two expert radiation oncologists independently evaluate the AI-generated contours of the CTVs and OARs, referencing international contouring guidelines. Contours are scored on a four-point Likert scale based on their clinical acceptability. In instances of disagreement, where one reviewer assigns an acceptable score and the other an unacceptable one, a third reviewer is consulted, and the final classification is determined by majority consensus.

Second, the dosimetric quality of each plan is assessed by comparing the calculated three-dimensional dose distribution and DVH metrics against predefined protocol-specific constraints. If any DVH constraint is not met, the plan undergoes further peer review to determine whether deviations are clinically justifiable, such as in cases involving complex tumour anatomy. If no justification is identified, the plan is classified as clinically unacceptable.

A plan is considered acceptable only if both its contours and dosimetry meet the established criteria. This approach ensures rigorous, standardised quality control of AI-generated plans across participating centres, without relying on patient outcomes or treatment delivery data (Aggarwal et al. [2023]).

Operational and economic evaluation

To evaluate the operational impact of AI-based planning, the ARCHERY study incorporates time-and-motion observations structured around the ESTRO-HERO TD-ABC model. Workflow components, including contouring and planning are timed separately for both the AI-assisted and conventional manual planning pathways. These time estimates are stratified by professional role and tumour site, and collected at each participating centre.

The TD-ABC model is used to estimate the resource use and associated costs of RT planning under both approaches. It includes direct resource inputs (e.g. personnel time, equipment usage, and treatment-specific consumables) as well as indirect institutional costs, such as infrastructure and maintenance. Centre-level data on staffing, equipment, and annual treatment volumes are integrated to contextualise cost estimates and allow comparisons across settings.

In addition to cost analysis, the study examines whether automation reduces clinician time spent on specific planning tasks. This is a significant consideration in low-resource environments where there is limited workforce capacity. These findings are synthesised into a cost impact analysis to assess the financial feasibility of AI-based planning implementation across different LMIC contexts (Aggarwal et al. [2023]).

3

Objectives and Methods

As the ARCHERY study is ongoing, complete results were not available within the time frame of this thesis. Consequently, the analysis is based exclusively on baseline data from the year 2022, derived from the ESTRO-HERO TD-ABC models developed independently by each participating centre prior to the implementation of the RPA.

3.1 Research objective

The primary objective of this master's thesis was to estimate the potential impact of AI-assisted RT planning on departmental costs and resource utilisation in LMICs. Utilising baseline data derived from the ESTRO-HERO TD-ABC models submitted by centres participating in the ARCHERY study, this work employs scenario-based simulations to quantify the effects of introducing the RPA into routine workflows.

As the ARCHERY study focuses exclusively on three tumour types (cervical, head and neck, and prostate cancer) and has not yet concluded at the time of this thesis, the analysis is based on pre-AI (2022) departmental models. These models represented clinical workflows prior to the introduction of AI tools in routine patient treatment. While the RPA was applied retrospectively as part of the ARCHERY study, its output did not influence actual patient care. For the purposes of this thesis, the pre-AI models were adapted to allow for tumour-type-specific time modifications, enabling the simulation of workflow changes that could occur if AI planning were to be implemented in the future. Three simulation scenarios were constructed to reflect varying assumptions about RPA integration,ranging from idealised time savings based on published literature, to more realistic conditions including QA, and finally, to a hypothetical department-wide adoption of AI across all tumour types and treatment techniques.

The overarching objective of this thesis was to explore how automation in treatment planning could influence the cost structure and resource allocation of RT services in settings with limited resources.

3.2 Data collection

Each participating RT centre collected baseline data from 2022 as part of their involvement in the ARCHERY study. Centres independently entered their data into the ESTRO-HERO TD-ABC tool and subsequently shared these data with the ARCHERY research team. The data provided by each centre included detailed inputs on departmental resource utilisation, such as personnel time allocation, equipment use, consumable materials, overhead expenses, and patient throughput (Defourny et al. [2022]). Its modular structure allows comparisons across tumour types, treatment techniques, and institutions, and makes it suitable for simulation-based scenario analysis.

The following section provides a detailed description of the specific data elements and the analytical structure of the ESTRO-HERO TD-ABC model.

3.2.1 ESTRO-HERO model implementation

The model was structured around three main layers: the EBRT-Core, the RO-Support layer and the Beyond-EBRT layer. While all three layers contributed to a comprehensive understanding of RT service delivery, the EBRT-Core was considered the most critical component of the ESTRO-HERO model overall, as it encompassed the core clinical workflow and accounted for the majority of resource use (Lievens and Grau [2012]). This focus was particularly relevant to the present analysis, given that the AI-based intervention, automated planning via the RPA, targeted key activities within this core layer.

The requisite inputs encompassed detailed information on departmental resources. With regard to equipment, this included the number of units used for imaging, treatment planning, and delivery, as well as infrastructure-related assets. Additional specifications such as unit price, annual maintenance contracts, and expected lifespan were also recorded for each equipment type. Personnel data encompassed staffing levels by role, gross annual salaries, contracted working hours, leave entitlements, and effective availability, including both clinical and support staff. Furthermore, information on consumables was collected, capturing patient-specific materials such as immobilisation masks and contrast media. Screenshots of the data entry interface used by

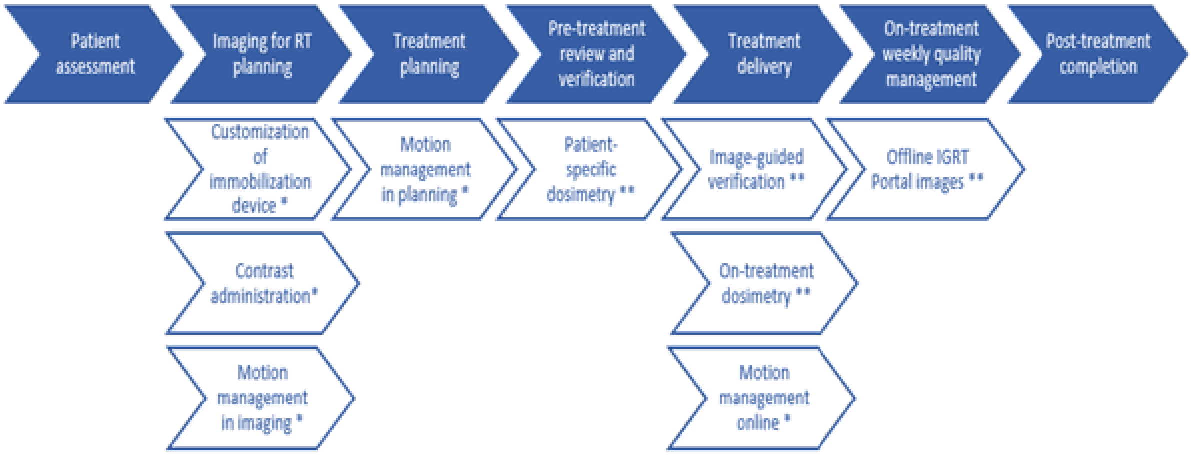


Figure 3.1: EBRT-Core care patient-related pathway within the ESTRO-HERO model. Optional steps indicated by asterisks vary based on tumour site, technique, or protocol.

participating centres to populate the model were included in Appendix A, illustrating the standardized format through which inputs were structured.

Each RT activity was then mapped along the care pathway, with associated estimates of the time required by each professional group (clinical, physics, imaging, planning and treatment delivery task group) to complete the activity. These time values were stratified by treatment technique to reflect variations across specific RT modalities, such as single-field RT, 2D conventional RT, 3D-CRT, IMRT, VMAT, and SBRT. Input data also included the number of EBRT treatment courses delivered by tumour type and intent, as well as the distribution of fractionation schedules and the frequency of optional workflow components, including image-guided RT and motion management. Finally, time estimates for activities not directly related to an individual patient in the RO-Support and Beyond-EBRT layers were also provided by staff for each relevant role.

The concept of an ”activity” served as the foundational unit of analysis within the model. An activity was defined as a discrete clinical or institutional task that consumes one or more resources over a measurable time interval. Activities were characterised by their timing (e.g. once per course, per week, or per fraction), their purpose within the workflow, and the personnel and equipment involved. In the EBRT-Core layer, these activities aligned with the ESTRO-HERO framework’s standardized RT pathway. The pathway is illustrated in Figure 3.1, which outlines the full sequence of patient-related steps from initial consultation to post-treatment review. The figure serves as a reference for the EBRT process and highlights the steps that are central to the cost and resource utilisation analysis presented in the following sections. Optional components of the pathway, such as on-treatment imaging or in vivo dosimetry, were incorporated selectively based on tumour site, treatment protocol, or departmental policy.

The calculation of costs in the EBRT-Core layer was performed using a TD-ABC formula. For each activity, the model multiplied the time allocated to each resource group by its CCR, which reflects the cost per available clinical minute. The CCR was computed by dividing the total annual cost of a resource, such as salaries for personnel, depreciation and service contracts for equipment, and allocated building costs, by the practical number of minutes the resource was available per year, adjusting for non-clinical time such as training, administrative work, and leave. The activity-level costs were then summed and combined with the cost of any associated consumables, as expressed in the following formula:

$$\text{Cost}_{\text{Activity}} = \sum_{r} (\text{Time}_r \times \text{CCR}_r) + \text{Consumables}$$

While this method was applicable to all EBRT-Core activities, the RO-Support and Beyond-EBRT layers were managed differently, given that they consisted of shared or non-patient-specific functions. The cost of these layers were initially calculated on an aggregate basis, and subsequently allocated across treatment courses in accordance with a standardised distribution rule. Specifically, 20% of the total cost was distributed proportionally based on the number of EBRT treatment courses, while the remaining 80% was allocated based on the number of fractions delivered. This 20/80 weighting reflected the combined impact of treatment volume and treatment intensity, and ensured that indirect costs are fairly attributed across patient cases (Defourny et al. [2019]).

The ESTRO-HERO model also produced a wide array of analytical outputs beyond cost estimates. It provided detailed breakdowns of total cost per activity, treatment technique, and tumour site; resource utilisation rates across professional groups and equipment categories; departmental throughput patterns; and the share of optional workflow elements used. A notable feature of the model is its dual costing approach, distinguishing between the spending-based and usage-based perspectives. The spending approach allocates the full cost of all available resources to treatment courses, regardless of whether those resources were fully utilized. This perspective reflects budgetary needs and infrastructure requirements to ensure service provision under peak capacity assumptions. In contrast, the usage approach includes only the proportion of resource costs directly consumed during care delivery, providing a more activity-specific view of operational efficiency. By applying both costing approaches, the present study was able to comprehensively assess the financial and resource implications of introducing the RPA into RT workflows. A summary of the model's core input parameters and analytical outputs is provided in Table 3.1.

3.3 AI impact assessment via simulations

This section delineates the adaptation of the baseline ESTRO-HERO models to simulate the potential impact of integrating an AI-based planning tool, designated the RPA, into routine RT workflows. The objective of this study was to estimate changes in resource utilisation and departmental costs associated with replacing selected manual processes with automated alternatives, specifically in the contouring and treatment planning stages of the EBRT-Core workflow.

3.3.1 Adaptations ESTRO-HERO model

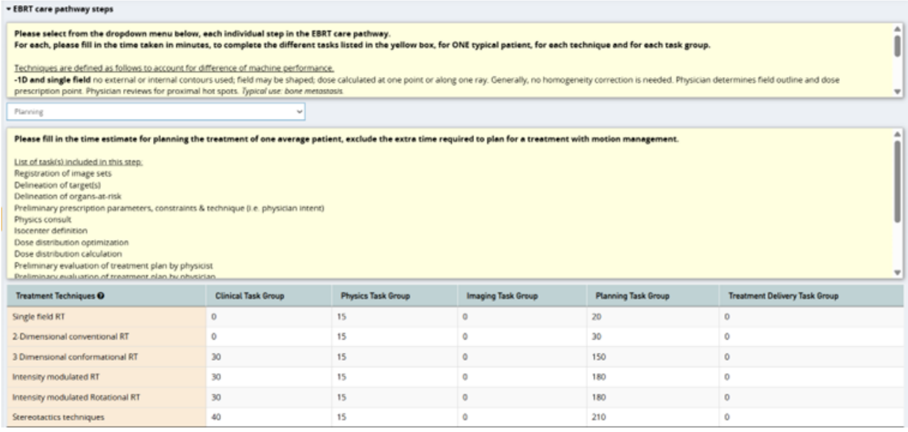
In the ESTRO-HERO TD-ABC model, the time allocated to each activity in the EBRT-Core pathway was differentiated by both treatment technique and task group, but not by tumour site. As illustrated in Figure 3.2, each activity (such as treatment planning) required centres to input time estimates for an average patient undergoing a given technique (e.g. IMRT, VMAT), subdivided by professional task group (e.g. planning, physics, imaging). However, the model architecture did not permit tumour-type-specific timing modifications within a given technique. This presented a challenge when attempting to simulate the impact of the RPA, as the ARCHERY study focuses exclusively on three tumour types: cervical, prostate, and head and neck cancers.

In order to isolate the effect of AI-based planning on only these tumour types without altering the timing for all other patients undergoing the same technique, the model required structural adaptation. A convenient solution was to create three duplicate techniques within the model, one for each of the treatment modalities commonly used for the ARCHERY tumour types. An analysis of the baseline models submitted by the participating centres revealed that cervical, prostate, and head and neck cases were planned using only three techniques: 3D-CRT, VMAT, and SBRT. Consequently, three novel custom techniques were devised and designated "$3D\_archery$," "$VMAT\_archery$," and "$STEREO\_archery$".

These newly developed techniques were structurally identical to their parent techniques, yet they permitted independent time entry for each task group, specific to the simulation

Table 3.1: Input parameters and key outputs of the ESTRO-HERO TD-ABC model

Category	Model Inputs	Model Outputs
Resources	• Inventory of equipment and infrastructure (e.g., imaging, planning, delivery systems) • Personnel profiles: staffing levels, roles, working hours, leave • List of consumables	• Distribution of personnel and equipment across model layers • Resource utilisation (e.g., CCR usage per task group)
Care Pathway	• EBRT workflow steps by treatment technique • Time required per activity and task group	• EBRT care structure and relative time burden • Activity-level costing per technique
EBRT Course Statistics	• Number of EBRT courses by tumour type, intent, technique • Frequency of optional protocol steps (e.g., IGRT, motion management)	• Distribution of EBRT workload across tumour types and techniques • Activation rates of optional steps
Support Activities	• RO-Support and institutional tasks (e.g., QA, admin, teaching) • Time allocation by support staff	• Allocation of indirect and support costs • Cost attribution by department function
Cost Data	• Cost rates applied to resources (e.g., salaries, equipment depreciation) • Building costs, overhead, and practical capacity constraints	• Spending-based and usage-based cost estimates • Costs per activity, per course, and per patient


▾ EBRT care pathway steps

Please select from the dropdown menu below, each individual step in the EBRT care pathway.
For each, please fill in the time taken in minutes, to complete the different tasks listed in the yellow box, for ONE typical patient, for each technique and for each task group.

Techniques are defined as follows to account for difference of machine performance.
-1D and single field no external or internal contours used; field may be shaped; dose calculated at one point or along one ray. Generally, no homogeneity correction is needed. Physician determines field outline and dose prescription point. Physician reviews for proximal hot spots. *Typical use: bone metastasis*

Planning

Please fill in the time estimate for planning the treatment of one average patient, exclude the extra time required to plan for a treatment with motion management.

List of task(s) included in this step:
Registration of image sets
Delineation of target(s)
Delineation of organs-at-risk
Preliminary prescription parameters, constraints & technique (i.e. physician intent)
Physics consult
Isocenter definition
Dose distribution optimization
Dose distribution calculation
Preliminary evaluation of treatment plan by physicist

Treatment Techniques	Clinical Task Group	Physics Task Group	Imaging Task Group	Planning Task Group	Treatment Delivery Task Group
Single field RT	0	15	0	20	0
2-Dimensional conventional RT	0	15	0	30	0
3 Dimensional conformational RT	30	15	0	150	0
Intensity modulated RT	30	15	0	180	0
Intensity modulated Rotational RT	30	15	0	180	0
Stereotactics techniques	40	15	0	210	0

Figure 3.2: Data entry interface of the ESTRO-HERO model showing the time allocation per task group for the activity "Treatment Planning." Values are differentiated by technique but not by tumour type.

of AI-related workflow changes. The total number of treatment courses and fractionation schedules remained unchanged from the original baseline models. The distribution of techniques across tumour types and fractionation schemes was preserved, but the proportion of cases corresponding to cervical, prostate, and head and neck cancers was reassigned to the corresponding ARCHERY techniques. This modification enabled the selective modification of activity times for only the subset of patients relevant to the simulation, while leaving the remainder of the model intact.

This adaptation allowed the simulation to reflect expected time savings from AI-assisted planning for the ARCHERY tumour types without overestimating its impact across the entire departmental workflow.

3.3.2 Simulations

In order to assess the potential operational and economic impact of introducing the RPA into clinical workflows, three simulation scenarios were developed using the adapted ESTRO-HERO TD-ABC models. Each simulation was designed to test different assumptions regarding AI-assisted planning, ranging from idealised time savings to more conservative, quality-controlled implementations. These simulations were applied to the subset of tumour types included in the ARCHERY study, as well as, in one case, to the full departmental workload.

Simulation 1: Literature-based time reductions
The initial simulation scenario aimed to represent the most likely outcome of the ARCHERY

study by modelling the implementation of the RPA and its expected effect on planning workflows.It drew upon existing literature reporting time savings achieved through the use of AI in both contouring and planning processes.Numerous studies have demonstrated significant reductions in manual workload across a range of tumour sites, with average time savings typically ranging from 65% to over 90%, depending on the tumour type, clinical context, and maturity of the AI solution(Court et al. [2024],Amjad et al. [2022],NICE [2023],Kalsi et al. [2024],Hoque et al. [2023],Byun et al. [2021]).

It was determined that, for all ARCHERY-related techniques, time inputs for planning-related EBRT-Core activities,specifically “*Planning*” and “*Motion Management in Planning*”, would be adjusted by 70%, 80%, and 90% time reduction to reflect the potential efficiency gains from AI integration. The 80% time reduction scenario was considered the primary simulation, while the 70% and 90% time reductions were included as part of a sensitivity analysis to explore the effect of varying levels of AI-driven time savings. These reductions were applied to all task groups involved in contouring and planning. Each of the three sub-scenarios was simulated independently, keeping all other model parameters constant. It is important to note that no additional time was allocated for verification or secondary review, reflecting a best-case scenario in which AI-generated plans are accepted without added workflow overhead.

Simulation 2: Time reductions with added quality review
The second simulation sought to emulate a more authentic clinical scenario, wherein the temporal advantages of automation are offset by the incorporation of supplementary QA measures. Preliminary findings from the ARCHERY study and analogous implementation studies suggest that departments frequently opt to incorporate a peer-review or verification stage when introducing AI-generated plans. This phenomenon is further corroborated by several reports, including guidelines from the Royal College of Radiologists and published reviews of AI deployment in LMIC settings, which emphasise the importance of clinical oversight to maintain treatment quality, particularly during early adoption (NICE [2023]).

To reflect this, a variation of Simulation 1 was constructed in which 10 minutes of additional time was added to the planning task group to account for independent plan checking. The values for these additional time periods were informed by published papers, where manual verification of AI contours is estimated to take between 5 and 20 minutes, depending on case complexity and site (Amjad et al. [2022],Court et al. [2018]). Time reductions for the planning activities ”*Planning*” and ”*Motion Management in Planning* ” remained at 80%, mirroring the main scenario from Simulation 1.

This simulation thus reflects a balanced, implementation-aware approach that combines efficiency gains with appropriate safety measures.

Simulation 3: Department-wide AI implementation
The final simulation extended the scope of AI integration to the entire RT department, removing the ARCHERY-specific technique adaptation and assuming that RPA could be applied across all tumour types and treatment modalities. In this scenario, an 80% time reduction was applied to ”*Planning*” and ”*Motion Management in Planning* ” across all task groups and all standard techniques (e.g. single field RT, 2D conformal RT, 3D-CRT, IMRT, VMAT, SBRT). This simulation represents a hypothetical future state in which AI planning is universally adopted and trusted, providing an upper-bound estimate of the system-wide efficiency and cost savings that could result from full departmental deployment of the RPA.

3.4 Data analysis and reporting

All analyses are based on the output of the ESTRO-HERO TD-ABC model and incorporate both usage-based and spending-based costing. Depending on where the impact is most meaningfully observed, either usage- or spending-based results are presented to best reflect changes in clinical resource consumption and financial expenditure.

Comparisons are made between the baseline model and each of the three simulation scenarios for all participating centres. The analysis focuses on changes in total departmental costs, costs per EBRT course and staff time allocation by task group.To facilitate comparison across countries, all cost values were converted to euros using the InforEuro exchange rate published by the European Commission for June 2022. This date was selected as it represents the midpoint of the reference year and aligns with the 2022 departmental data used in the models (exc).To summarise the variation between centres, the following descriptive statistics are reported: mean percentage change and standard deviation. These provide insight into the consistency and variability of the simulated effects across different institutional settings.

Results are presented using a combination of tables and graphical visualisations. Comparative tables show both absolute and relative differences between scenarios, while stacked bar charts are used to illustrate shifts in the distribution of costs and time across clinical activities and professional roles. As the analysis is based on deterministic model outputs rather than empirical sampling, no inferential statistical tests are applied.

4

Results

Of the six participating centres, only four completed the ESTRO-HERO TD-ABC model within the time frame of this master's thesis. These included the King Hussein Cancer Centre (Jordan), University Malaya Medical Centre (Malaysia), Groote Schuur Hospital (South Africa), and Tata Medical Centre, Kolkata (India) (Table 4.1). The remaining two centres were excluded from further analysis due to delayed data submission. For the centres reporting costs in local currency, all values were converted to euros using the InforEuro exchange rates from the European Commission for June 2022. The applied conversion rates were as follows: 1 Malaysian Ringgit (MYR) = 0.21278 EUR, 1 Jordanian Dinar (JOD) = 1.31032 EUR, and 1 South African Rand (ZAR) = 0.06007 EUR. Data from the Indian centre were already provided in euros and thus required no conversion. Subsequent analyses focus on the distribution of resource use and costs across the defined steps of the EBRT care pathway. Readers seeking clarification on the composition of these steps are referred to Figure 3.1

Table 4.1: Participating RT centres that completed the ESTRO-HERO TD-ABC model within the time frame of this thesis and corresponding countries.

Centre name	**Country**
King Hussein Cancer Centre	Jordan
University Malaya Medical Centre	Malaysia
Groote Schuur Hospital	South Africa
Tata Medical Centre, Kolkata	India

4.1 Baseline results

This section summarises the pre-intervention landscape across the four centres, focusing on three domains: departmental characteristics, resource utilisation and a detailed cost breakdown. Together, these baseline data frame the challenges and opportunities for introducing AI–assisted planning.

4.1.1 Departmental characteristics

Patient volume and treatment intent

As demonstrated in Table 4.2, there is considerable heterogeneity in the annual EBRT course volumes across the four centres. Tata Medical Centre,Kolkata, reported the highest patient throughput, with 2,978 EBRT courses administered annually, followed by Grote Schuur (1,214), King Hussein Cancer Centre (864) and University Malaya Medical Centre (815). Overall, curative indications predominate at the South African (97.0%) and the Indian centre (77.2%), while the Malaysian (40.0%) and the Jordanian centre (47.1%) both have substantial palliative workloads. The mean fractions per course demonstrate significant variation, with values of 30.3 at King Hussein Cancer Centre, 20.9 at Groote Schuur Hospital, 17.3 at Tata Medical Centre, and 13.7 at University Malaya Medical Centre, reflecting the varying composition of treatment protocols.

Table 4.2: Overview of EBRT course volumes, treatment intent, and average fractionation per course across the participating centres.

Centre	Grote Schuur Hospital	King Hussein Cancer Centre	University Malaya Medical Centre	Tata Medical Centre, Kolkata
EBRT Courses	1214	864	815	2978
% Curative	97.0	52.9	60.0	77.2
% Palliative	3.0	47.12	40.0	22.8
Avg. Fractions	20.9	30.3	13.7	17.3

Tumour site and technique distribution

Figure 4.1 presents the tumour type distribution across the participating centres. Table 4.3 complements this by detailing the technical approach and fractionation strategies employed at each site.

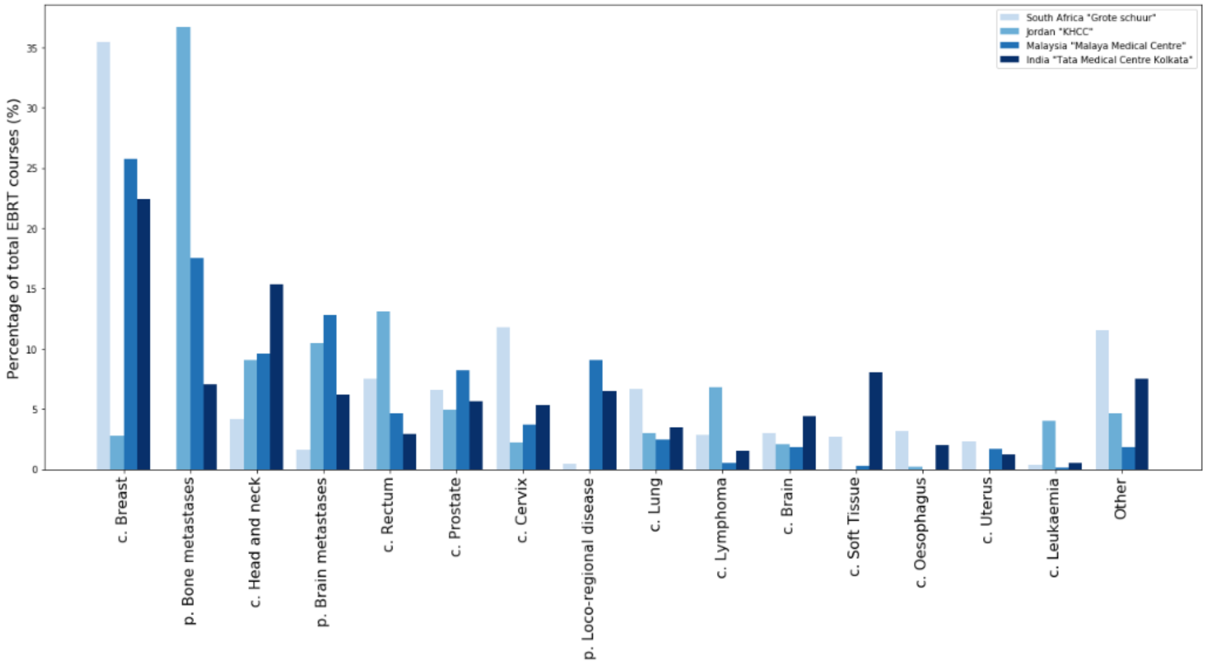


Figure 4.1: Distribution of tumour sites treated with EBRT across the four study centres.

Across the four centres the caseload is dominated by five tumour groups: breast Cancer (accounting for roughly one-quarter to one-third of all EBRT courses), bone metastases (0–37%, underscoring the sizeable palliative workload), head-and-neck malignancies (4–15%), brain metastasis (2–12%) and rectal Cancers (3–13%). Cervical Cancer, prostate Cancer, and loco-regional disease are also prominent across centres, with average EBRT shares slightly below that of rectal Cancer but still within a similar range. Tumour sites that exhibit a minimal contribution, typically less than 5%, encompass the following: lung, lymphoma, oesophagus, uterus and soft tissue. To preserve readability of the main figure, any tumour site whose average share of EBRT courses is < 1% has been aggregated into the composite category 'Other'. Figure 2 in Appendix B shows the distribution of all the incidence sites.

The centres display markedly different technology profiles, as seen in Table 4.3. Grote Schuur Hospital employs a broadly modern approach in which VMAT predominates (57.8%) but is complemented by substantial use of 3D-CRT (39.6%) and minimal application of 2D RT (2.6%). King Hussein Cancer Centre similarly relies on VMAT (50.1%) while retaining a nearly equal share of 3D-CRT (48.8%) and almost no use of 2D techniques (0.1%). University Malaya Medical Centre follows a more conventional approach, delivering the majority of treatments with 3D-CRT (73.0%) and using VMAT in less than a quarter of cases (23.8%). Tata Medical Centre, Kolkata, by contrast, is

Table 4.3: Distribution of RT techniques across the four study centres. Values represent the percentage of EBRT courses delivered using each technique. A value of 0% indicates that the technique is not in use at the respective centre.

Centre	Grote Schuur Hospital	King Hussein Cancer Centre	University Malaya Medical Centre	Tata Medical Centre, Kolkata
Single field RT (%)	0.0	0.0	0.0	1.4
2D RT (%)	2.6	0.1	0.4	16.1
3D-CRT (%)	39.6	48.9	73.0	12.9
IMRT (%)	0.0	0.0	0.1	2.5
VMAT (%)	57.8	50.1	23.8	65.0
SBRT (%)	0.0	1.0	2.7	2.2

highly arc-oriented, with VMAT representing 65.0% of its treatments, yet it also shows the highest reliance on legacy 2D RT (16.1%) and the only use of single-field techniques (1.4%). Across all centres, SBRT remains limited, comprising less than 3% of treatments in any department.

Equipment and staffing resources

Table 4.4 shows the technological and human resources available at each site. All four centres had four linear accelerators (LINACs), with the exception of University Malaya Medical Centre, which had two. In particular, the number of treatment planning systems (TPS) varied considerably, with Tata Medical Centre, Kolkata, and Grote Schuur Hospital maintaining seven systems each, compared to only one in University Malaya Medical Centre and King Hussein Cancer Centre.

Staffing structures revealed further differences in the distribution and composition of the workforce. The South African centre employed 17 ROs with no trainees, while the Malaysian centre's clinical group included 9 ROs and 28 trainees, and the Indian centre operated with 6 ROs, 3 nurses and 17 fellows. Physicists ranged from 2 (at the South African centre) to 13 (at the Jordanian centre), and the planning group in Tata Medical Centre Kolkata, included both physicists and dosimetrists (10 each), reflecting a more mixed staffing model. Treatment delivery teams were similarly diverse, ranging from 12 RTTs in University Malaya Medical Centre to 33 RTTs plus 2 physicists in Grote Schuur Hospital.

Table 4.4: Technological infrastructure and staffing composition across RT centres. Equipment counts include LINACs, CT simulators, and treatment planning systems (TPS). Staff roles are listed by task group and expressed in full-time equivalents (FTE).

Centre	Grote Schuur Hospital	King Hussein Cancer Centre	University Malaya Medical Centre	Tata Medical Centre, Kolkata
LINACs	4	4	2	4
CTs	2	2	1	1
TPS	7	1	1	7
Clinical task group	17 RO	14 RO	9 RO + 28 trainee RO	6 RO + 3 nurses + 17 fellows
Physics task group	2 physicists	13 physicists	3 physicists	10 physicists
Imaging task group	4 RTT	2 dosimetrists	12 RTT	22 RTT
Planning task group	4 RTT + 2 physicists	15 RTT	5 physicists	10 dosimetrists + 10 physicists
Treatment delivery	33 RTT + 2 physicists	33 RTT	12 RTT	22 RTT

4.1.2 Resource utilisation

Planning time per technique

Table 4.5 presents the average planning time per RT technique across the participating centres. Simpler techniques, such as Single Field and 2D-RT, generally required the least planning time. Single Field RT was not in clinical use at Groote Schuur Hospital, King Hussein Cancer Centre, or University Malaya Medical Centre, hence a planning time of 0 minutes was recorded at these centres. Only Tata Medical Centre, Kolkata, reported use of Single Field RT, with an average planning time of 35 minutes. For 2D-RT, planning times ranged from 10 minutes in the Malaysian centre to 60 minutes in the Indian one. Substantial differences were observed in planning time for more advanced techniques. The Malaysian centre reported the highest values, with 1,260 minutes for both IMRT and VMAT, and 1,380 minutes for SBRT. In contrast, Tata Medical Centre,Kolkata, and Groote Schuur Hospital reported shorter durations for these modalities (ranging from 225 to 390 minutes), while King Hussein Cancer Centre consistently indicated 300 minutes for each advanced technique.

Table 4.5: Average planning time (in minutes) per RT technique across participating centres.

Centre	Grote Schuur Hospital	King Hussein Cancer Centre	University Malaya Medical Centre	Tata Medical Centre, Kolkata
Single Field	0	0	0	35
2D-RT	55	60	10	45
3D-CRT	225	120	195	195
IMRT	240	300	1260	225
VMAT	390	300	1260	225
SBRT	375	300	1380	265

Equipment utilisation

Figure 4.2 illustrates the estimated need or surplus of key equipment types across centres, based on the available units and the estimated equipment needs derived from time allocations for each step in the EBRT care pathway. Positive values indicate surplus capacity, while negative values highlight equipment shortages.

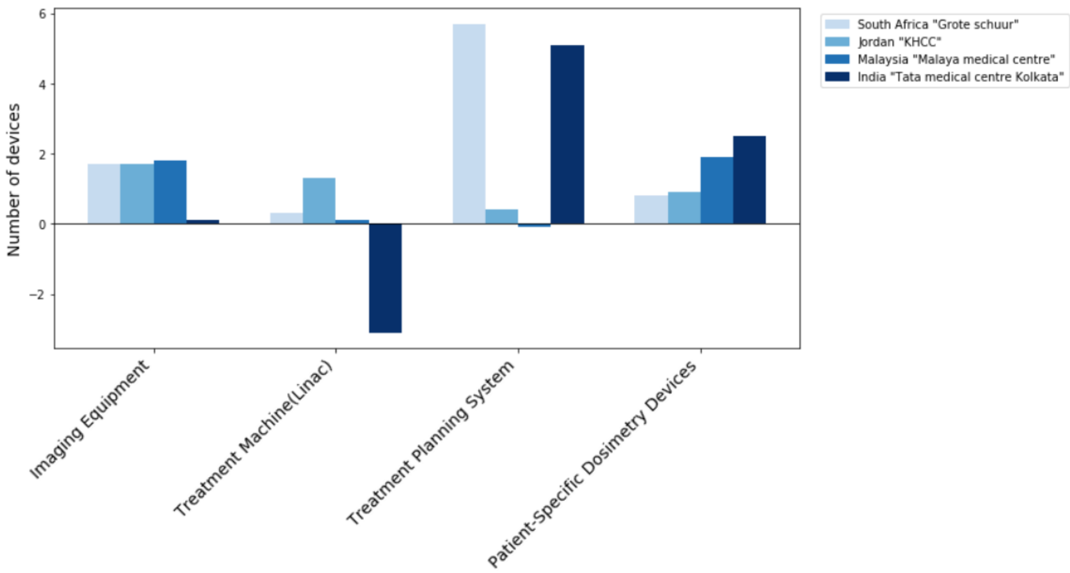


Figure 4.2: Modelled equipment surplus and shortfall by centre, based on the available units and the estimated equipment needs derived from time allocations for each step in the EBRT care pathway. Surplus (positive) and need (negative) are expressed in equivalent full-capacity units for TPS, LINACs, imaging devices, and patient-specific dosimetry tools.

A notable surplus of TPS was observed at Groote Schuur Hospital (+5.7 units) and Tata Medical Centre, Kolkata (+5.1 units), indicating underutilised planning infrastructure. The King Hussein Cancer Centre demonstrated a modest TPS surplus of 0.4 units, while the University Malaya Medical Centre exhibited a marginal deficit of -0.1 units. The utilisation of LINACs varied notably across centres. Tata Medical Centre, Kolkata, exhibited a substantial shortfall of −3.1 units. In contrast, the King Hussein Cancer Centre and Groote Schuur Hospital operated close to their estimated requirements, while the University Malaya Medical Centre maintained modest surpluses. The distribution of imaging equipment among the three institutions was found to be relatively balanced, with each institution reporting a surplus of approximately +1.8 units. The Tata Medical Centre, Kolkata, has achieved a relatively balanced position in this area. Patient-specific dosimetry tools were underutilised across all sites, although surpluses were recorded at Tata Medical Centre, Kolkata (+2.5 units), and University Malaya Medical Centre (+1.9 units).

Table 4.6: Top three equipment-related time drivers at each centre (percentage of total equipment time in parentheses). IGRT = image-guided radiotherapy; “On. IGRT & localisation” refers to online guidance and patient positioning before treatment.

Resource type	**Rank**	Grote Schuur Hospital	King Hussein Cancer centre	Malaya Medical centre	Tata Medical centre, Kolkata
Equipment	1	Planning (38.2%)	Treatment delivery (47.4%)	Planning (56.1%)	Treatment delivery (34.7%)
	2	Treatment delivery (35.3%)	Planning (29.4%)	Treatment delivery (19.7%)	Planning (31.8%)
	3	On. IGRT & localisation (10.6%)	Review & verification (6.2%)	On. IGRT & localisation (10.9%)	On. IGRT & localisation (13.2%)

Complementing these findings, Table 4.6 highlights the distribution of equipment time across EBRT care pathway steps. Planning emerged as the most equipment-intensive phase at the Malaysian centre (56.1%) and the South African centre (38.2%), likely reflecting higher planning complexity or specific workflow practices. In contrast, treatment delivery accounted for the largest share of equipment time at the Jordanian (47.4%) and Indian (34.8%) centres. Online image-guided verification and localization also contributed significantly to equipment utilisation, particularly at the Malaysian (10.9%), Indian (13.2%), and South African (10.6%) centres. Pretreatment review and planning review had a smaller, though still notable, impact on equipment time at the Jordanian centre, indicating variations in workflow structure across sites.

Personnel utilisation

Personnel utilisation patterns varied considerably across centres, reflecting differences in treatment complexity, patient throughput, and staffing models.

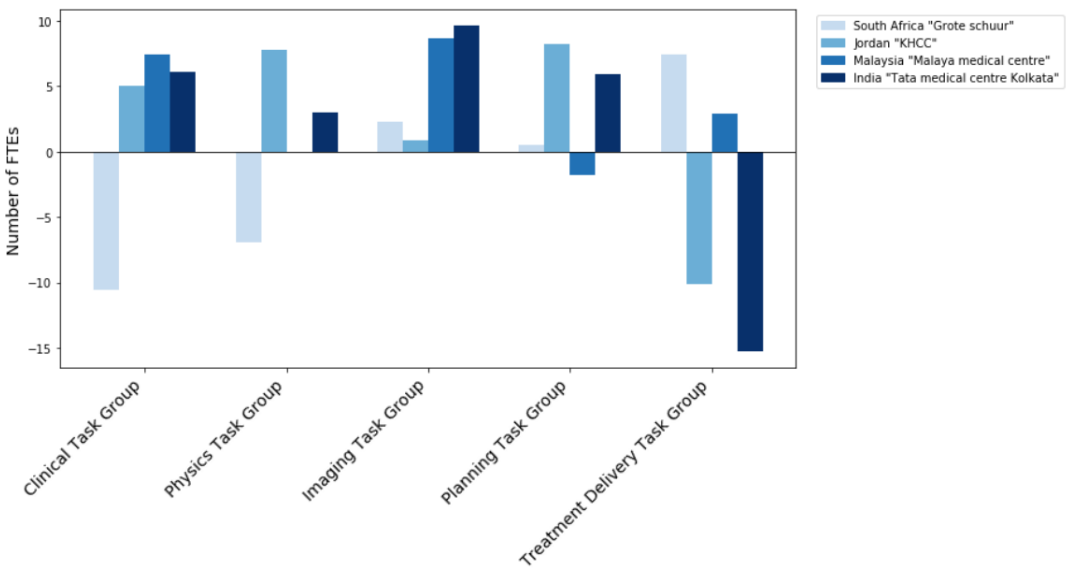


Figure 4.3: Modelled personnel surplus and shortfall by centre, based on the available FTEs and the estimated personnel needs derived from time allocations for each step in the EBRT care pathway. Surplus (positive) and need (negative) are expressed in full-time equivalents (FTEs) for clinical, physics, planning, and treatment delivery staff.

Figure 4.3 shows the estimated surplus or deficit of personnel, expressed in full-time equivalents (FTEs), across major task groups, based on the available FTE and the estimated personnel needs derived from time allocations for each step in the EBRT care pathway. Groote Schuur Hospital exhibited significant deficits in both the clinical (–10.6 FTEs) and physics task groups (–6.9 FTEs), suggesting pressure on core planning and oversight roles. In contrast, King Hussein Cancer Centre, University Malaya Medical Centre, and Tata Medical Centre, Kolkata, reported surpluses in these areas, with King Hussein Cancer Centre notably over-resourced in physics (+7.8 FTEs).

The planning task group displayed distinct differences across centres. University Malaya

Medical Centre faced a notable deficit of –1.8 FTEs, highlighting strain in handling planning workloads, whereas King Hussein Cancer Centre (+8.2 FTEs) and Tata Medical Centre, Kolkata (+5.9 FTEs), exhibited clear surpluses. Groote Schuur Hospital remained near balance (+0.5 FTE). Treatment delivery staff deficits were most pronounced at Tata Medical Centre, Kolkata (–15.3 FTEs), and King Hussein Cancer Centre (–10.1 FTEs). Groote Schuur Hospital and University Malaya Medical Centre had positive staffing levels in treatment delivery (+7.4 and +2.9 FTEs, respectively).

Table 4.7 details the top three personnel time-share drivers across the participating centres. Planning was consistently among the top three time-consuming activities at all centres, underscoring its central role in the EBRT workflow. Treatment delivery consumed the largest share of personnel time across all sites, ranging from 31.3% at the Malaysian centre to 64.4% at the Jordanian centre. Planning ranked second at the Malaysian (29.8%) and Jordanian (10.0%) centres, reflecting the resource burden of high-complexity planning tasks. Online image guidance and localisation also accounted for a substantial portion of personnel time, particularly at the Malaysian (18.9%), Indian (15.9%), and South African (13.7%) centres. The full distribution of time-share allocations for both equipment and personnel across EBRT steps can be found in Figure 3 of Appendix B.

Table 4.7: Top three personnel-related time drivers at each centre (percentage of total equipment time in parentheses). IGRT = image-guided radiotherapy; "On. IGRT & localisation" refers to online guidance and patient positioning before treatment.

Resource type	**Rank**	Grote Schuur Hospital	King Hussein Cancer centre	Malaya Medical centre	Tata Medical centre, Kolkata
Personnel	1	Treatment Delivery (55.4%)	Treatment Delivery (64.4%)	Treatment Delivery (31.3%)	Treatment Delivery (41.8%)
	2	On. IGRT & localisation (13.7)	Planning (10.0%)	Planning (29.8%)	On. IGRT & localisation (15.9%)
	3	Planning (12.0%)	On. IGRT & localisation (5.7%)	On. IGRT & localisation (18.9%)	Planning (12.3%)

4.1.3 Cost breakdown

Total and per-patient spending

Total annual spending on EBRT varies widely across centres (Table 4.8). Groote Schuur Hospital reports the highest annual cost at €6.71 million, followed closely by Tata Medical Centre, Kolkata (€6.24 million), and University Malaya Medical Centre (€5.97 million), while King Hussein Cancer Centre operates on a more modest budget of €3.29 million. Although EBRT pathway activities dominate costs at all centres, their internal composition varies considerably. University Malaya Medical Centre and King Hussein Cancer Centre are highly equipment-focused, allocating 70.5% and 88.4% of EBRT costs to equipment, respectively. Groote Schuur Hospital stands out as more labour-intensive, with 14.3% of EBRT spending attributed to personnel, while Tata Medical Centre, Kolkata, falls in between at 11.1%. Consumables represent a minor share of overall EBRT costs across all centres, ranging from 0.1% to 3.7%.

Table 4.8: Total annual spending-based departmental costs by centre, with breakdown of expenditures across major cost categories. (incl. EBRT, RO Support and Non-EBRT cost)

Resource	Grote Schuur Hospital	King Hussein Cancer Centre	Malaya Medical Centre	Tata Medical Centre, Kolkata
Total (€)	6,705,830.35 (100%)	3,294,495.58 (100%)	5,974,790.21 (100%)	6,243,337.42 (100%)
EBRT care pathway steps (€)	3,940,800.51 (58.8%)	3,138,870.60 (95.3%)	4,859,698.79 (81.3%)	5,259,421.56 (84.2%)
Equipment (€)	2,912,746.42 (43.4%)	2,911,439.23 (88.4%)	4,212,813.27 (70.5%)	4,511,037.42 (72.3%)
Personnel (€)	957,247.18 (14.3%)	106,724.69 (3.2%)	643,237.41 (10.8%)	692,053.38 (11.1%)
Consumables (€)	70,806.91 (1.1%)	120,706.68 (3.7%)	3,648.11 (0.1%)	56,330.76 (0.9%)
RO Support (€)	1,778,061.14 (26.5%)	113,236.12 (3.4%)	524,869.25 (8.8%)	798,713.27 (12.8%)
Non-EBRT Care (€)	986,968.69 (14.7%)	42,388.85 (1.3%)	590,222.17 (9.9%)	185,202.60 (3.0%)

Unit costs, however, do not mirror the total spending hierarchy (Table 4.9). The Malaysian centre reports the highest average cost per EBRT course (€7,191), with an exceptionally high maximum of €42,506 that exceeds the other centres by far. This is followed by the South African centre (€5,524), the Jordanian centre (€3,276), and the Indian centre (€3,007). A similar ranking is observed for cost per fraction, which ranges from €526 at the Malaysian centre to just €145 at the Jordanian centre. These differences reflect variations in fractionation practices and staffing models across centres.

Table 4.9: Average cost per EBRT course and per fraction by centre, based on total departmental expenditures. Costs include EBRT pathway activities, RO-support, and non-EBRT care. Reported values reflect the average, minimum, and maximum observed across all treatment courses.

Country	Cost per EBRT course (€)			Cost per EBRT fraction (€)		
	Average	Min	Max	Average	Min	Max
Grote Schuur Hospital	5,523.74	1,017.95	8,864.17	264.37	210.00	1,684.60
King Hussein Cancer Centre	3,276.25	323.65	10,833.76	145.45	114.00	1,767.63
University Malaya Medical Centre	7,191.10	1,477.29	42,505.64	526.38	89.00	6,122.68
Tata Medical Centre,Kolkata	3,007.00	466.00	29,168.00	174.00	77.00	2,071.00

Technique-driven variation and cost drivers

Technique choice significantly influences spending-based cost variation across centres (Figure 4.4). Across all centres, there is a clear trend of increasing cost with more advanced RT techniques. At Groote Schuur Hospital, the cost of a 3D-CRT course (€4,283) is more than double that of 2D-RT (€1,608), with VMAT rising to €6,553. At University Malaya Medical Centre, this gradient is even steeper: VMAT costs (€15,582) are more than tenfold higher than 2D-RT (€1,506), and nearly quadruple those of 3D-CRT (€4,599). At King Hussein Cancer Centre and Tata Medical Centre, Kolkata, advanced techniques also cost more than simpler ones, but overall remain more affordable, with VMAT ranging between €3,879 and €5129, and IMRT below €2,500 in both centres.

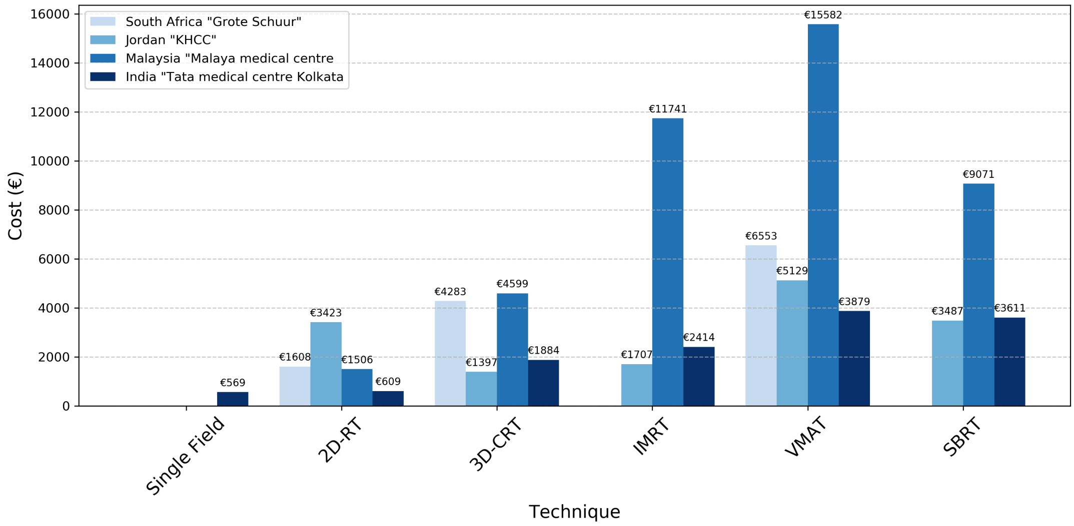


Figure 4.4: Average spending-based cost per EBRT course by RT technique and centre. Costs include EBRT care pathway activities, RO support, and non-EBRT care. Bars represent the average total cost per course for each technique at the four centres.

Figure 4.5 shows the average spending-based EBRT planning cost per course across RT techniques and centres. Planning costs generally increase with technique complexity. For 2D-RT, costs range from €46 at the Jordanian centre to €200 at the Indian centre. In 3D-CRT, the Indian centre again reports the highest cost (€867), while the Jordanian centre remains lowest (€91). The Malaysian centre records the highest planning costs for both IMRT and VMAT (€1,355 each), followed by the Indian centre (€1,000). The South African centre reports a VMAT planning cost of €860 but does not report values for IMRT or SBRT. For SBRT, the Malaysian centre leads with €1,532, followed by the Indian centre at €1,178.

Cost-driver analysis (Table 4.10) provides further insight into spending patterns across centres. Treatment delivery equipment is the leading cost driver in three centres: King Hussein Cancer Centre (79%), Groote Schuur Hospital (47%), and University Malaya Medical Centre (38%). At Tata Medical Centre, Kolkata, however, planning is the primary equipment cost driver, accounting for 52% of equipment spending. Planning also ranks second at Groote Schuur Hospital (26%) but accounts for just 7% and 6% at the Jordanian and Malaysian centres, respectively. Personnel cost patterns differ. Planning accounts for the highest share of personnel costs at University Malaya Medical Centre (35%) and Tata Medical Centre, Kolkata (25%). In contrast, Groote Schuur Hospital and King Hussein Cancer Centre allocate the largest personnel shares to treatment

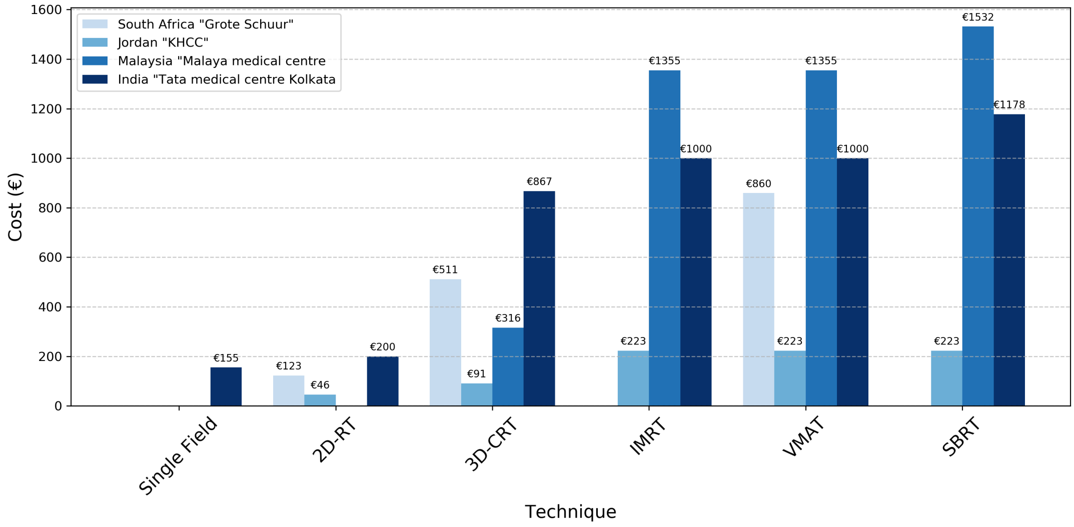


Figure 4.5: Average EBRT spending-based planning cost within the EBRT care pathway per course by technique and centre. Missing bars indicate that the technique was not in clinical use at the respective centre.

delivery (55% and 30%, respectively). Notably, online image guidance and localisation (On. IGRT & localisation) is consistently among the top three personnel cost drivers in all centres except Jordan, where offline IGRT ranks higher.

Spending vs. usage-based costing

When comparing total annual costs, usage-based estimates were consistently lower than spending-based Figures across all centres. The total for the South African centre dropped from €6.71M to €6.34M, the Jordanian centre from €3.29M to €2.84M, the Malaysian centre from €5.97M to €3.97M, and the Indian centre from €6.24M to €5.08M. These reductions reflect the discrepancy between recorded expenditures and actual clinical workload, particularly in centres with underutilised equipment or staff.

Despite the drop in total costs, the rank order of centres by cost remained unchanged. The Malaysian centre remained the most expensive site per EBRT course. Cost drivers remained broadly similar: treatment delivery continued to dominate both equipment and personnel costs, though staff time was more heavily weighted under usage-based modelling, especially at the South African and Indian centres.

For detailed breakdowns of usage-based cost categories, per-technique costs, and cost

Table 4.10: Top three spending-based cost drivers by resource type and centre for EBRT pathway activities only. Values reflect the share of total spending within each resource category (equipment and personnel). IGRT = image-guided radiotherapy; “On. IGRT & localisation” refers to online guidance and patient positioning before treatment.

Resource type	**Rank**	Grote Schuur Hospital	King Hussein Cancer centre	Malaya Medical centre	Tata Medical centre, Kolkata
Equipment	1	Treatment delivery (47%)	Treatment delivery (79%)	Treatment delivery (38%)	Planning (52%)
	2	Planning (26%)	On. IGRT & localisation (7%)	On. IGRT & localisation (21%)	Treatment delivery (21%)
	3	On. IGRT & localisation (14%)	Dosimetry (4%)	Imaging (21%)	Review & verification (11%)
Personnel	1	Treatment delivery (55%)	Treatment delivery (30%)	Planning (35%)	Planning (25%)
	2	On. IGRT & localisation (19%)	Planning (26%)	On. IGRT & localisation (16%)	Treatment delivery (16%)
	3	Imaging (10%)	Offline IGRT(21%)	Imaging (14%)	Patient assessment (11%)

drivers, see Tables 3–4-5 and Figures 4–5 in Appendix B.

4.2 Simulation 1

Simulation 1 evaluated the potential impact of the RPA by applying planning time reductions of 70%, 80%, and 90% for ARCHERY-specific tumour types (cervical, head and neck, and prostate Cancers). Unless otherwise specified, all tables and figures in this section refer to the 80% planning time reduction scenario, which serves as the primary condition for Simulation 1.

4.2.1 Resource impact

Planning time

At an 80% reduction scenario, planning time significantly decreased, translating into considerable time savings per patient, especially in centres with initially higher baseline planning durations (Table 4.11).

Table 4.11: Average planning time per technique (in minutes) at each centre under AI-based planning time reductions of 70%, 80%, and 90%. Values are shown as (90%) 80% (70%), with the 80% scenario reflecting the main simulation condition. Techniques include ARCHERY-specific tumour types: 3D-CRT, IMRT, and SBRT.

Technique	Grote Schuur Hospital	King Hussein Cancer centre	Malaya Medical centre	Tata Medical centre, Kolkata
3D_archery	(22.5) 45 (67.5)	(12) 24 (36)	(19.5) 39 (58.5)	(19.5) 39 (58.5)
IMRT_archery	(24) 48 (72)	(30) 60 (90)	(126) 252 (378)	(22.5) 45 (67.5)
STEREO_archery	(37.5) 75 (112.5)	(30) 60 (90)	(138) 276 (414)	(26.5) 53 (79.5)

Equipment utilisation

Table 4.12 outlines the TPS capacity and corresponding demand across the four centres under baseline and AI-assisted planning scenarios. At baseline, the Malaysian centre operated above its TPS capacity (1.1 units required for one available), but under all three AI-based planning scenarios from Simulation 1, this demand fell below 1.0 unit, resolving the shortfall. The South African and Indian centres also experienced reductions in TPS demand of up to 0.4 units. On average, the 80% planning-time reduction scenario led to a decrease of 0.3 TPS units across centres (SD = 0.2).

Table 4.12: TPS availability and estimated demand across centres under baseline conditions and three AI-assisted planning scenarios (70%, 80%, and 90% planning time reduction). Values indicate the number of full-capacity TPS units required, based on patient workload and planning time assumptions.

Metric	Grote Schuur Hospital	King Hussein Cancer centre	Malaya Medical centre	Tata Medical centre, Kolkata
TPS Available	7	1	1	7
TPS Needed (baseline)	1.3	0.6	1.1	1.9
TPS Needed (-80%)	1.1	0.6	0.7	1.4
TPS Needed (-70%)	1.1	0.6	0.7	1.5
TPS Needed (-90%)	1	0.6	0.6	1.4

Changes in equipment time allocation under the 80% planning time reduction scenario are presented in Table 4.13. The top three equipment-related tasks remained unchanged in rank across all centres, although minor variations in their relative time shares were observed due to the simulation. Planning time decreased at all centres, with an average reduction of 5.9% (SD = 3.4%). The largest reduction was recorded at University Malaya Medical Centre (–10.5%). In contrast, equipment time allocated to treatment delivery increased across all centres, with a mean increase of 4.1% (SD = 1.5%). Time dedicated to online IGRT and localisation also rose modestly, by an average of 2.0% (SD = 0.9%). No outliers were identified for these latter two categories.

The sensitivity of equipment-time distribution to varying levels of AI-driven planning-time reduction was analysed across three scenarios (70%, 80%, and 90%) within Simulation 1. At all centres, the top three tasks: treatment delivery, planning, and online IGRT & localisation (or review & verification at King Hussein Cancer Centre) maintained their rank irrespective of the extent of planning-time reduction (Tables 4.13 and 1 in Appendix B). However, the relative share of equipment time allocated to each task varied slightly between scenarios, with an average absolute shift of just 0.55 % (SD = 0.45%) between the 70% and 80% reduction, and 0.53% (SD = 0.48%) between the 80% and 90% reduction. Overall, planning time occupied a marginally smaller share under the 90% scenario, averaging 1.6% less compared to the 70% scenario, with a maximum individual centre difference of 3.6% observed at University Malaya Medical Centre. Consequently, treatment delivery and online IGRT & localisation or review tasks showed modest relative increases under deeper planning-time reductions. Detailed percentage values for the 70% and 90% scenarios are presented in Table 1 of Appendix B.

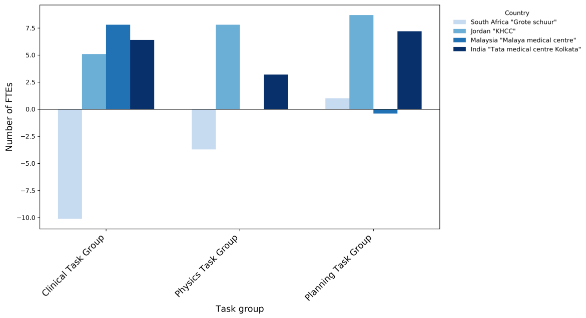
Table 4.13: Top three equipment-related time drivers at each centre under the 80% planning time reduction scenario (Simulation 1). Values indicate the percentage of total equipment time allocated to each task. IGRT = image-guided radiotherapy; “On. IGRT & localisation” refers to online guidance and patient positioning before treatment.

Resource type	**Rank**	Grote Schuur Hospital	King Hussein Cancer centre	Malaya Medical centre	Tata Medical centre, Kolkata
Equipment	1	Treatment delivery (40.00%)	Treatment delivery (49.4%)	Planning (45.6%)	Treatment delivery (38.8%)
	2	Planning (32.8%)	Planning (27.2%)	Treatment delivery (25.2%)	Planning (26.4%)
	3	On. IGRT & localisation (12.0%)	Review & verification (5.9%)	On. IGRT & localisation (14.0%)	On. IGRT & localisation (14.7%)

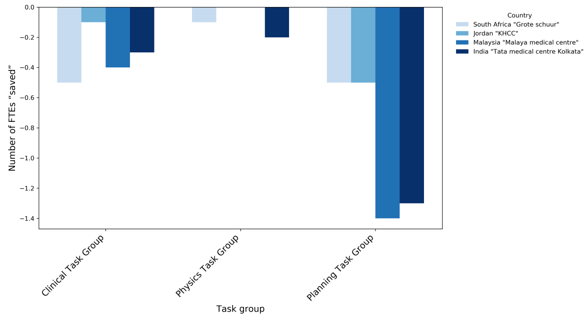
Personnel utilisation

Simulation 1 projected meaningful shifts in personnel requirements across the clinical, physics, and planning task groups, with the most pronounced impact observed in planning. Compared to the baseline scenario (Figure 4.3), Figure 4.6a shows that existing workforce bottlenecks remained largely unchanged under the 80% planning time reduction; centres with baseline staff shortages continued to face constraints.

The right panel (Figure 4.6b) illustrates the absolute reduction in required FTEs per task group. Planning showed the greatest decline, with demand decreasing by an average of 0.9 FTEs per centre (SD = 0.4 FTE). Clinical staffing requirements declined by 0.3 FTEs on average (SD = 0.2 FTE), while the physics group exhibited minimal change (average reduction: 0.1 FTEs; SD = 0.1 FTE. Although most centres achieved meaningful efficiency gains in planning, the Malaysian centre retained a small planning deficit, indicating that even substantial improvements in planning efficiency may not fully resolve workforce limitations in under-resourced environments.



(a) Net personnel surplus (positive values) or shortage (negative values),based on the available FTEs and the estimated personnel needs derived from time allocations for each step in the EBRT care pathway, across centres and task groups under Simulation 1 (80% planning time reduction).



(b) Absolute reduction in required FTEs per task group under Simulation 1 (80% planning time reduction), compared to baseline staffing estimates. Negative values indicate a decrease in FTE demand.

Figure 4.6: Estimated impact of AI-based planning automation (Simulation 1, 80% time reduction) on personnel resource needs across centres. Left panel shows the net surplus or deficit in FTEs per task group relative to baseline staffing levels. Right panel illustrates the absolute reduction in FTE demand per task group, comparing baseline and simulated conditions.

Although AI-based planning time reductions led to measurable changes in staffing demand, the overall impact was modest and largely confined to the planning task group. As shown in Figure 4.7, all four centres demonstrated a gradual reduction in required planning FTEs as planning time decreased from 70% to 90%. At University Malaya Medical Centre, planning demand declined from 3.4 to 3.1 FTE; at Tata Medical Centre, Kolkata from 4.1 to 3.8 FTE; at King Hussein Cancer Centre from 4.1 to 3.9 FTE; and at Groote Schuur Hospital from 2.2 to 2.1 FTE. By contrast, the level of clinical staffing remained consistent across all scenarios, for example 10.3 FTE at Groote Schuur Hospital and 5.5 FTE at Tata Medical Centre. Physics staffing also showed no variation, with centres such as University Malaya Medical Centre and King Hussein Cancer Centre maintaining baseline values of 0.0 and 0.6 FTE, respectively. These findings suggest that while planning automation can reduce staffing needs in specific areas, the differences between 70%, 80%, and 90% planning time reduction scenarios are relatively small, and are unlikely to lead to meaningful staffing changes at the departmental level.

Time-share analysis in Table 4.14 further illustrates the shifts in personnel allocation observed under the 80% planning time reduction scenario. The composition of the top

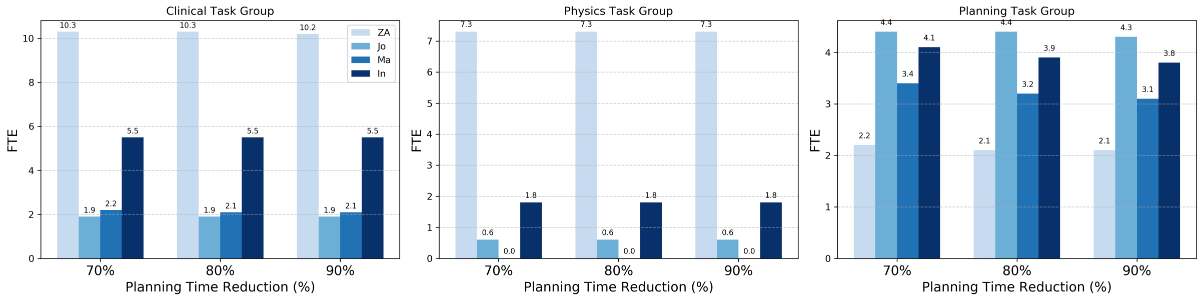


Figure 4.7: FTE staffing requirements by task group and centre under simulated planning time reductions (70%, 80%, and 90%). Planning-related FTEs decline with greater time savings, while clinical and physics staffing remain stable across scenarios.

three personnel time-share drivers remained consistent across most centres, with the exception of the Malaysian centre, which showed a change in rank between planning and treatment delivery. These results reinforce that the most substantial efficiency gains are expected at the Malaysian centre, owing to its initially long planning durations.

Planning time as a proportion of total personnel time decreased by an average of 4.0% across centres (SD = 4.0%), with reductions ranging from –1.0% at the Jordanian centre to –9.9% at the Malaysian centre. Conversely, the share of time spent on treatment delivery increased by an average of 2.2% (SD = 1.4%), with centre-specific changes ranging from +0.9% at the Jordanian centre to +4.1% at the Malaysian centre. Time allocated to online IGRT and localisation remained largely stable, with changes below 1% at all centres except the Malaysian centre.

The sensitivity of personnel-time allocation to different levels of AI-driven planning-time reduction (70%, 80%, and 90%) within Simulation 1 was assessed, revealing stable rankings among the top three personnel tasks at all centres (Tables 4.14 and 2 in Appendix B). While the relative positions of treatment delivery, planning, and online IGRT & localisation remained unchanged, small shifts in their percentage shares occurred. The average absolute change between 70% and 80% scenarios was only 0.35% (SD = 0.29%), and similarly minor between 80% and 90% (average = 0.32%, SD = 0.28%). Comparing the extremes (70% to 90%), the average shift was 0.67% (SD = 0.55%), with the largest single observed shift being an increase of 1.20% for treatment delivery at University Malaya Medical Centre. As anticipated, higher levels of automation (90%) resulted in slightly reduced planning shares and modestly increased proportions for treatment delivery and online IGRT & localisation. Detailed percentage values for the 70% and 90% scenarios are presented in Appendix B Table 2

Table 4.14: Top three personnel-related time drivers at each centre under the 80% planning time reduction scenario (Simulation 1). Values indicate the percentage of total equipment time allocated to each task. IGRT = image-guided radiotherapy; "On. IGRT & localisation" refers to online guidance and patient positioning before treatment.

Resource type	**Rank**	Grote Schuur Hospital	King Hussein Cancer centre	Malaya Medical centre	Tata Medical centre, Kolkata
Personnel	1	Treatment Delivery (57.4%)	Treatment Delivery (65.3%)	Treatment Delivery (35.5%)	Treatment Delivery (43.5%)
	2	ON. IGRT & localisation (14.2%)	Planning (9.0%)	Planning (21.7%)	On. IGRT & localisation (16.5%)
	3	Planning (9.7%)	On. IGRT & localisation (5.8%)	On. IGRT & localisation (21.4%)	Planning (9.9%)

4.2.2 Cost impact

Total cost and cost drivers

In Simulation 1, spending-based departmental costs remained unchanged across all centres. However, under the usage-based approach, where resource use is linked to time allocation, total costs declined modestly in all the centres. It led to an average reduction of -2.5% (SD = 1.3%) in total usage-based departmental costs (Table 4.15). The greatest relative decrease was observed in the Indian centre, where usage-based costs declined from €5,079,846.02 to €4,894,942.22 (-3.6%). The Malaysian centre reported a decrease from €3,965,629.11 to €3,866,972.26 (-2.5%), while the South African centre saw a reduction from €6,338,165.77 to €6,144,119.86 (-3.1%). In the Jordanian centre, total usage-based costs decreased from €2,839,770.25 to €2,818,725.38 (-0.7%). These reductions reflect decreased planning time for only the ARCHERY tumour types—cervix, prostate, and head & neck—leaving much of the departmental workflow unaffected. Equipment-related EBRT costs declined from €2,557,883.81 to €2,502,154.02 in the Malaysian centre (-2.2%) and from €3,435,681.67 to €3,276,746.91 in the Indian centre (-4.6%). Personnel costs showed similar changes: in the Malaysian centre, costs dropped from €289,005.77 to €246,078.71 (-14.9%), and in the Indian centre, from €603,917.73 to €577,948.68 (-4.3%). No reductions were observed in consumables, RO support, or non-EBRT care.

The average cost per EBRT course and per fraction, derived from the spending-based approach, remained unchanged. Small differences in the minimum and maximum values, typically within a few euros, were recorded but did not reflect meaningful shifts in cost structure.

The sensitivity analysis of usage-based annual departmental costs across the 70%, 80%, and 90% planning-time reduction scenarios demonstrated minimal variation. Total usage-based costs remained highly stable, with differences of less than 1% observed between the 70% and 90% scenarios at all centres. These results indicate that departmental resource requirements are robust to incremental changes in partial planning efficiency.

Table 4.15: Simulation 1: Total annual usage-based departmental costs by centre under 80% planning time reduction, with breakdown of expenditures across major cost categories (incl. EBRT, RO Support, and Non-EBRT care).

Resource	Grote Schuur Hospital	King Hussein Cancer centre	Malaya Medical centre	Tata Medical centre, Kolkata
Total(€)	6,144,119.86 (100%)	2,818,725.38 (100%)	3,866,972.26 (100%)	4,894,942.22 (100%)
EBRT care pathway steps	3,379,090.02 (54.9%)	2,623,145.26 (94.4%)	2,751,880.84 (71.2%)	3,911,026.35 (79.8%)
Equipment(€)	1,857,113.08 (30.2%)	2,346,603.25 (84.4%)	2,502,154.02 (64.7%)	3,276,746.91 (66.9%)
Personnel(€)	1,500,710.06 (24.4%)	167,835.34 (5.9%)	246,078.71 (6.4%)	577,948.68 (11.8%)
Consumables(€)	21,266.88 (0.3%)	120,706.68 (4.3%)	3,648.11 (0.1%)	56,330.76 (1.1%)
RO Support(€)	1,778,061.14 (28.9%)	113,236.12 (4.0%)	524,869.25 (13.6%)	798,713.27 (16.3%)
Non-EBRT Care(€)	986,968.69 (16.1%)	42,388.85 (1.5%)	590,222.17 (15.3%)	185,202.60 (3.8%)

Although the total EBRT pathway spending-based cost remained constant under the 80% planning-time reduction scenario in Simulation 1, the internal distribution of these costs across workflow components shifted modestly. The share of planning in EBRT-related expenditures declined in most centres. On average, planning accounted for 3.5% less of the EBRT equipment costs (SD = 4.4%), while its share of personnel costs decreased by 3.4% on average (SD = 1.9%). These shifts reflect the partial reduction in planning time for ARCHERY tumour types.

With regard to equipment-related cost drivers (Table 4.16), task rankings remained unchanged across all centres compared to the baseline scenario. The largest decline in planning-related equipment cost share was observed at the Indian centre (–9%), where this decrease was primarily absorbed by an increase in review and verification activities

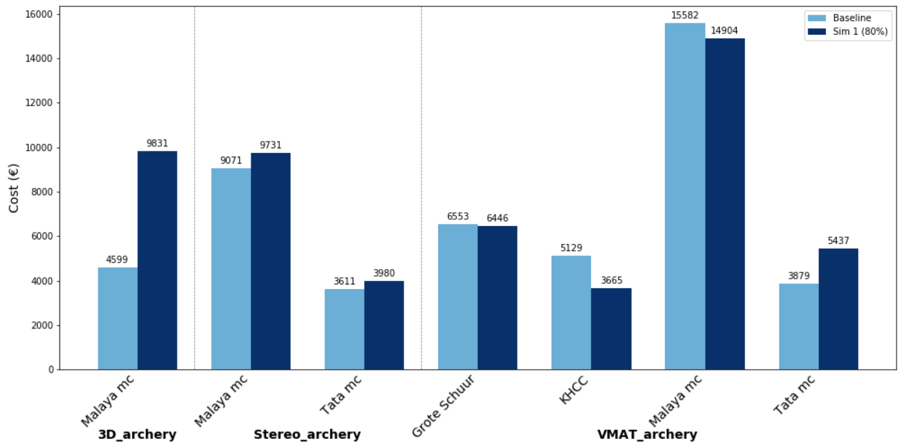


Figure 4.8: Simulation 1 (80% planning time reduction): average cost per EBRT course by technique for ARCHERY tumour sites, across centres. Costs include EBRT pathway activities, RO support, and non-EBRT care. MC = Medical Centre.

(+8%). In contrast, no change in equipment driver composition was noted at the Jordanian or Malaysian centres, as planning was not part of their top three equipment-related cost drivers in either the baseline or simulated scenarios. This may reflect infrastructure differences, as both centres operate with only one TPS unit, compared to seven at the South African and Indian centres. At Groote Schuur Hospital, the decline in planning's equipment share was redistributed among other EBRT steps.

In terms of personnel-related cost drivers (Table 4.16), task rankings also remained largely stable across centres. While no new tasks entered the top three at any centre, one positional shift was noted at the Jordanian centre, where planning moved to third place behind offline IGRT. The overall reduction in planning's cost share was modestly absorbed by other EBRT tasks. As a result, several centres exhibited slight increases (typically 1–2%) in the share of personnel costs allocated to tasks other than treatment delivery, which itself remained stable throughout the simulation.

When comparing the 70% and 90% planning-time reduction scenarios, no differences were observed in the composition or ranking of the top three cost drivers for either equipment or personnel. Given that the changes under the 80% scenario were already modest, a further 10% increase or decrease in planning-time reduction had only minimal additional impact. These findings suggest that, within the tested range, the cost structure is relatively insensitive to incremental changes in planning efficiency.

Table 4.16: Simulation 1 (80% planning time reduction): top three spending-based cost drivers by resource type and centre for EBRT pathway activities. Values reflect the share of total spending within each resource category (equipment and personnel). IGRT = image-guided radiotherapy; “On. IGRT & localisation” refers to online guidance and patient positioning before treatment.

Resource Type	Rank	Grote Schuur Hospital	King Hussein Cancer centre	Malaya Medical centre	Tata Medical centre, Kolkata
Equipment	1	Treatment delivery (47%)	Treatment delivery (79%)	Treatment delivery (38%)	Planning (43%)
	2	Planning (21%)	On. IGRT & localisation (7%)	On. IGRT & localisation (21%)	Treatment delivery (21%)
	3	On. IGRT & localisation (14%)	Dosimetry (4%)	Imaging (21%)	Review & verification (19%)
Personnel	1	Treatment delivery (55%)	Treatment delivery (30%)	Planning (29.6%)	Planning (22%)
	2	On. IGRT & localisation (19%)	Offline IGRT (22%)	On. IGRT & localisation (18%)	Treatment delivery (16%)
	3	Imaging (10%)	Planning (22%)	Imaging (15%)	Patient assessment (12%)

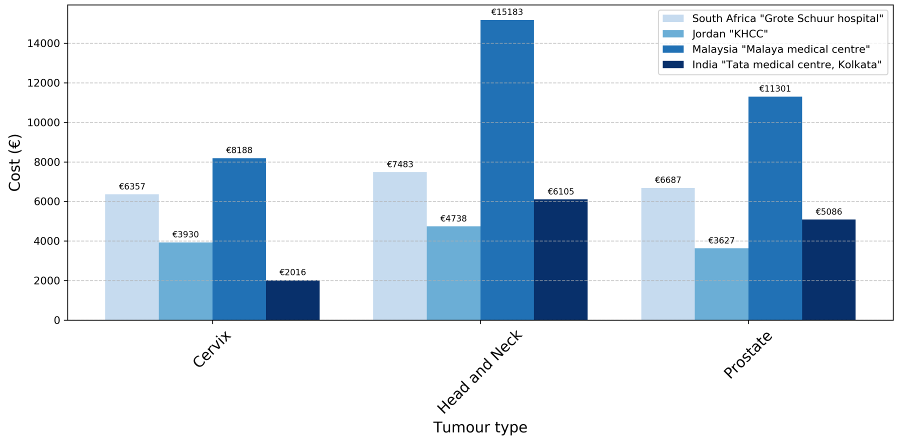


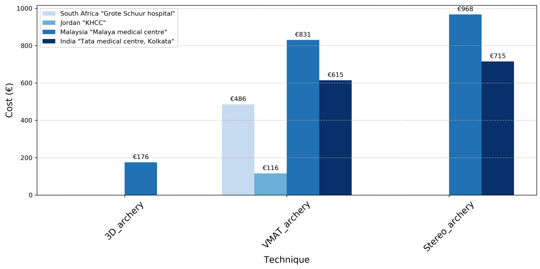
Figure 4.9: Simulation 1 (80% planning time reduction): average spending-based cost per EBRT course by tumour type (cervical, head and neck, and prostate Cancer) for ARCHERY study cases. Costs reflect EBRT pathway activities only.

Technique driven and tumour site variation

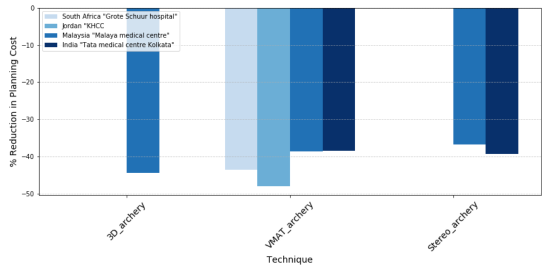
Under Simulation 1 (80% planning time reduction), spending-based EBRT course costs for ARCHERY tumour sites showed heterogeneous effects across techniques and centres (Figure 4.8). On average, a +9.0% change in EBRT cost per course was observed across all techniques and centres (SD = 25.9%), with several combinations showing cost increases rather than reductions. The most substantial increase occurred for 3D-CRT at the Malaysian centre, where average course costs rose from €4,599 to €9,831 (+113.8%). More modest increases were noted for stereotactic techniques, including an increase at the Indian centre from €3,611 to €3,980 (+10.2%), and at the Malaysian centre from €9,071 to €9,731 (+6.8%). VMAT was the only technique to exhibit consistent cost reductions across most centres, with decreases of 4.4% at the Malaysian centre, 1.6% at Groote Schuur Hospital, and 28.5% at King Hussein Cancer Centre. In contrast, the Indian centre reported a VMAT cost increase from €3,879 to €5,437 (+28.7%).

Figure 4.9 presents the average spending-based cost per EBRT course by tumour type (cervical, head and neck, and prostate Cancer) under Simulation 1 (80% planning time reduction), based solely on EBRT pathway costs. Across all centres, Simulation 1 led to an average cost reduction of 5.9% (SD = 6.9%) for ARCHERY tumour sites. The largest decreases were observed at Tata Medical Centre, Kolkata, where cervical Cancer costs declined by 22.0% (from €2,585 to €2,016), followed by reductions of 11.7% for head and neck and 8.4% for prostate Cancer. University Malaya Medical Centre also demonstrated consistent decreases across all three tumour types, with reductions of 8.1% for cervical, 7.5% for head and neck, and 12.2% for prostate. At King Hussein Cancer Centre, average EBRT course costs increased slightly: +1.7% for cervical, +0.6% for head and neck, and +0.3% for prostate. Groote Schuur Hospital showed modest cost reductions for all tumour types, ranging from 1.2% to 2.3%. These findings highlight that planning automation may reduce EBRT costs for high-complexity tumour sites, though local infrastructure and baseline planning effort shape the magnitude of impact.

The sensitivity analysis revealed that planning-time reduction had only a modest effect on spending-based EBRT costs under partial AI implementation. For ARCHERY technique EBRT course costs (Figure 4.8), the average difference between the 70% and 80% planning-time reduction scenarios was 2.3% (SD = 0.98%), while the difference between the 80% and 90% scenarios was slightly lower at 1.9% (SD = 0.85%). A similar pattern was observed for average EBRT course costs by tumour type (Figure 4.9), with an average difference of 1.5% (SD = 0.45%) between the 70% and 80% reductions and 1.7% (SD = 0.74%) between the 80% and 90% levels. These findings suggest that departmental EBRT costs remain relatively stable despite incremental changes in planning efficiency.



(a) Average EBRT planning cost per treatment course by technique under Simulation 1 (80% planning reduction). Costs reflect only the EBRT pathway (i.e., excluding RO support and non-EBRT activities) and are shown for each participating centre.



(b) Percentage reduction in planning cost per EBRT course by technique under Simulation 1(80% planning time reduction) compared to baseline. Negative values indicate cost savings resulting from automation-related planning time reductions.

Figure 4.10: Impact of Simulation 1 (80% planning time reduction) on planning-related EBRT course costs across centres. Subfigure (a) shows absolute planning costs per technique, while Subfigure (b) shows the relative reduction compared to baseline.

Planning costs per technique under Simulation 1 (80% planning time reduction) for

ARCHERY tumour types are presented in Figure 4.10a. These values reflect spending-based EBRT costs for the planning component only, disaggregated by RT ARCHERY technique. Across all centres and modalities, the average planning cost per EBRT course was €584 (SD = €277). The highest values were observed for stereotactic planning at University Malaya Medical Centre (€968) and Tata Medical Centre, Kolkata (€715). VMAT planning costs were similarly elevated at the Malaysian centre (€831), moderate at the Indian centre (€615), and lower at Groote Schuur Hospital (€486) and King Hussein Cancer Centre (€116). For 3D-CRT, only the Malaysian centre reported relevant planning costs (€176), as the other centres do not apply this technique to the ARCHERY tumour types.

The relative reductions in planning costs compared to baseline are shown in Figure 4.10b. Across centres and techniques, the average reduction in planning cost was 41.5% (SD = 4.2%). For VMAT, the largest decline occurred at King Hussein Cancer Centre (–48.1%), followed by reductions above 40% at Groote Schuur Hospital, Tata Medical Centre, and University Malaya Medical Centre. Stereotactic planning costs decreased by 38.5% at the Indian centre and 36.9% at the Malaysian centre. A reduction for 3D-CRT was reported only at University Malaya Medical Centre (–44.4%).

The sensitivity analysis of planning costs per technique further illustrates the effect of varying levels of planning-time reduction on spending-based EBRT costs for ARCHERY tumour types. As shown in Figure 4.10b, the relative difference in planning cost per technique was more pronounced than for overall EBRT course costs. Between the 70% and 80% planning-time reduction scenarios, the average difference in planning cost per technique was 13.7% (SD = 4.3%), while the difference between 80% and 90% was 11.4% (SD = 5.2%). These findings indicate that while absolute planning costs decrease substantially under automation, the incremental cost savings between different planning-time reduction levels tend to taper off.

4.3 Simulation 2

4.3.1 Resource impact

Simulation 2 evaluated the impact of incorporating a 10-minute QA check into the planning workflow, designed to reflect a more realistic clinical verification process. The addition of this QA time did not alter overall equipment utilisation patterns or personnel allocation. TPS demand remained unchanged across all four centres, and no measurable variation was seen in FTE staffing requirements. Task-group time shares also remained stable. These results indicate that short QA procedures can be integrated into the planning pathway without creating measurable operational burden at the departmental level.

4.3.2 Cost impact

The inclusion of the 10-minute QA step had a minimal cost impact, limited only to a slight increase in the unit price of the pretreatment review and verification activity for the ARCHERY techniques. All other departmental costs, including those related to personnel, equipment, and consumables, remained unchanged.

4.4 Simulation 3

4.4.1 Resource impact

Equipment utilisation

Table 4.17: Simulation 3: TPS availability and estimated demand at each centre under baseline conditions and an 80% planning time reduction scenario applied to all tumour types. Values indicate the number of full-capacity TPS units required, based on patient workload and planning time assumptions.

Metric	Grote Schuur Hospital	King Hussein Cancer centre	Malaya Medical centre	Tata Medical centre, Kolkata
TPS Available	7	1	1	7
TPS Needed (Baseline)	1.3	0.6	1.1	1.9
TPS Needed (-80%)	0.5	0.2	0.3	0.7

Simulation 3 applied the same AI-driven planning support as Simulation 1 but extended the planning time reduction to all tumour types across the department (Table 4.17). This scenario resulted in substantial reductions in TPS demand across all centres. At the 80% planning time reduction level, average TPS need decreased by 0.8 units (SD = 0.3 units) compared to baseline, bringing all centres well below their available TPS capacity. For example, the Indian centre's TPS demand dropped from 1.9 to 0.7 units, and the

Malaysian centre's from 1.1 to 0.3 units, effectively resolving the planning infrastructure bottleneck previously observed.

Table 4.18: Top three equipment-related time drivers at each centre under the 80% planning time reduction scenario (Simulation 3). Values indicate the percentage of total equipment time allocated to each task. IGRT = image-guided radiotherapy; "On. IGRT & localisation" refers to online guidance and patient positioning before treatment.

Resource type	**Rank**	Grote Schuur Hospital	King Hussein Cancer centre	Malaya Medical centre	Tata Medical centre, Kolkata
Equipment	1	Treatment delivery (51.0%)	Treatment delivery (62.7%)	Treatment delivery (35.0%)	Treatment delivery (46.5%)
	2	On. IGRT & localisation (15.3%)	Review & verification (10.1%)	Planning (20.0%)	On. IGRT & localisation (17.6%)
	3	Review & verification (13.3%)	Planning (7.8%)	On. IGRT & localisation (19.4%)	Review & verification (11.1%)

Simulation 3 produced a more pronounced shift in equipment time allocation compared to Simulation 1, where task rankings remained unchanged. As shown in Table 4.18, the expansion of AI-driven planning time reduction to all tumour types led to clear reordering of task priorities across centres.

At Groote Schuur Hospital and Tata Medical Centre, Kolkata, planning-related equipment use no longer appeared among the top three contributors. In contrast, King Hussein Cancer Centre and University Malaya Medical Centre retained planning in their top three, although its relative rank dropped by one position, replaced by the task previously ranked just below. Across all centres, the average proportion of equipment time dedicated to planning fell by 27.2% (SD = 6.5%), with the largest reduction observed at University Malaya Medical Centre (–36.1%). Specifically, planning time at Groote Schuur Hospital declined from 38.2% to 10.7%, and at Tata Medical Centre from 31.8% to 8.4%.

Treatment delivery emerged as the leading driver of equipment use in all centres, with an average increase of 13.8% (SD = 1.8%). Online IGRT and localisation rose to second place at both Groote Schuur Hospital and Tata Medical Centre, with an average increase of 5.0% (SD = 2.6%). In both centres, review and verification entered the top three, replacing planning as a key contributor to equipment time.

Personnel utilisation

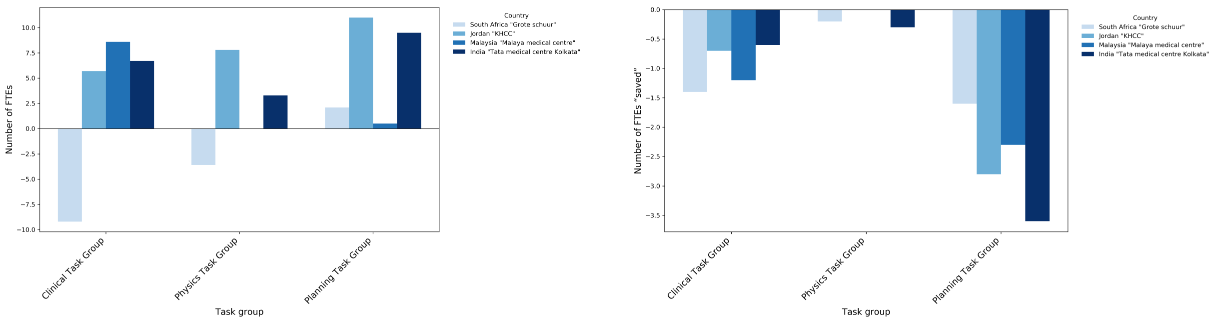
Simulation 3 projected more substantial shifts in personnel requirements compared to Simulation 1, particularly within the planning task group. As planning time reductions were extended to all tumour types, the effect on personnel resources became more pronounced. Compared to the baseline scenario, Figure 4.11a shows that the planning-related personnel bottleneck at University Malaya Medical Centre was resolved, resulting in a small surplus of 0.5 FTEs. In contrast, staffing constraints within the clinical and physics task groups remained largely unchanged, reflecting the more modest impact of planning time reductions on those domains.

The right panel (Figure 4.11b) illustrates the absolute reduction in required FTEs per task group relative to baseline. The largest effect was observed in the planning group, with an average decrease of 2.6 FTEs per centre (SD = 0.8 FTE). The most significant reductions occurred at University Malaya Medical Centre (–2.8 FTE) and Tata Medical Centre, Kolkata (–3.6 FTE). The clinical task group experienced a moderate decrease in demand, averaging 1.0 FTE per centre (SD = 0.4 FTE). The smallest change was seen in the physics task group, with negligible reductions at most centres. This limited impact is attributable to the fact that only Groote Schuur Hospital and Tata Medical Centre, Kolkata allocate planning responsibilities to the physics team to a minor extent.

Simulation 3 resulted in a more substantial reallocation of personnel time across task groups compared to Simulation 1. As shown in Table 4.19, extending the planning time reduction to all tumour types led to a noticeable reordering of personnel task priorities across centres.

Planning was no longer among the top three personnel time drivers in three out of the four centres; only University Malaya Medical Centre retained planning within its top-ranked activities. On average, the share of personnel time dedicated to planning decreased by 12.3% (SD = 6.5%). The largest reduction was observed at University Malaya Medical Centre, where planning time fell from 29.8% to 7.8% (–22.0 %). Comparable declines were recorded at Tata Medical Centre, Kolkata (from 12.8% to 2.8%, –10.0 %), Groote Schuur Hospital (from 12.0% to 2.7%, –9.3 %), and King Hussein Cancer Centre (from 10.0% to 2.2%, –7.8 %).

Across all centres, treatment delivery emerged as the leading contributor to personnel



(a) Net personnel surplus (positive values) or shortage (negative values),based on the available FTEs and the estimated personnel needs derived from time allocations for each step in the EBRT care pathway, across centres and task groups under Simulation 3 (80% planning time reduction).

(b) Absolute reduction in required FTEs per task group under Simulation 3 (80% planning time reduction), compared to baseline staffing estimates. Negative values indicate a decrease in FTE demand.

Figure 4.11: Estimated impact of AI-based planning automation (Simulation 3, 80% time reduction) on personnel resource needs across centres. Left panel shows the net surplus or deficit in FTEs per task group relative to baseline staffing levels. Right panel illustrates the absolute reduction in FTE demand per task group, comparing baseline and simulated conditions

time, increasing by an average of 6.5% (SD = 2.0%). Online IGRT and localisation consistently held the second position, with an average increase of 2.4% (SD = 2.3%). The task that replaced planning in the top three varied by centre, reflecting local workflow differences. At Groote Schuur Hospital, quality management entered the top three; at King Hussein Cancer Centre, the replacement tasks was offline IGRT; and at Tata Medical Centre, imaging became the third most time-consuming activity.

Table 4.19: Top three personnel-related time drivers at each centre under the 80% planning time reduction scenario (Simulation 3). Values indicate the percentage of total equipment time allocated to each task. IGRT = image-guided radiotherapy; "On. IGRT & localisation" refers to online guidance and patient positioning before treatment.

Resource type	**Rank**	Grote Schuur Hospital	King Hussein Cancer centre	Malaya Medical centre	Tata Medical centre, Kolkata
Personnel	1	Treatment Delivery (61.3%)	Treatment Delivery (70.2%)	Treatment Delivery (40.8%)	Treatment Delivery (46.5%)
	2	On. IGRT & localisation (15.2%)	On. IGRT & localisation (6.2%)	On. IGRT & localisation (24.6%)	On. IGRT & localisation (17.7%)
	3	Quality management (5.4%)	Offline IGRT (5.8%)	Planning (7.8%)	Imaging (7.5%)

4.4.2 Cost impact

Total and per-patient spending

Although Simulation 3 did not affect the totals for fixed departmental spending, which remain constant under the spending-based model, the cost estimates based on usage decreased in three of the four centres. Table 4.20 presents these cost changes, with average usage-based departmental costs falling by 3.7% (SD = 4.9%) compared to baseline. The largest relative reduction occurred at the Indian centre, where total costs declined from €5,079,846.02 to €4,583,784.24, a 9.8% decrease. The Malaysian centre reported a 5.1% reduction, with costs decreasing from €3,965,629.11 to €3,764,655.41. At the Jordanian centre, the change was minimal, from €2,839,770.25 to €2,812,077.20

(–1.0%). In contrast, the South African centre showed a slight increase in usage-based costs, rising from €6,338,165.77 to €6,376,790.37 (+0.6%). Although overall costs slightly increased in the South African centre, minor internal reallocations of resource use were observed across all centres. For example, at the Indian centre, equipment costs declined from €3,435,681.67 to €3,007,657.76, and personnel costs from €603,917.73 to €535,879.85.

Table 4.20: Simulation 3: total annual usage-based departmental costs by centre under 80% planning time reduction, with breakdown of expenditures across major cost categories (incl. EBRT, RO Support, and Non-EBRT care).

Resource	Grote Schuur Hospital	King Hussein Cancer centre	Malaya Medical centre	Tata Medical centre, Kolkata
Total(€)	6,376,790.37 (100%)	2,812,077.20 (100%)	3,764,655.41 (100%)	4,583,784.24 (100%)
EBRT care pathway steps	3,611,760.54 (56.6%)	2,656,452.21 (94.5%)	2,649,563.99 (70.4%)	3,599,868.37 (78.5%)
Equipment(€)	1,662,754.67 (26.1%)	2,379,775.72 (84.4%)	2,446,776.68 (65.0%)	3,007,657.76 (65.6%)
Personnel(€)	1,927,738.99 (30.2%)	155,971.05 (5.9%)	199,139.20 (5.3%)	535,879.85 (11.7%)
Consumables (€)	21,266.88 (0.3%)	120,706.68 (4.3%)	3,648.11 (0.1%)	56,330.76 (1.2%)
RO Support(€)	1,778,061.14 (27.9%)	113,236.12 (4.0%)	524,869.25 (13.9%)	798,713.27 (17.4%)
Non-EBRT Care(€)	986,968.69 (15.5%)	42,388.85 (1.5%)	590,222.17 (15.7%)	185,202.60 (4.0%)

In Table 4.21, average spending-based costs per EBRT course remained fixed under Simulation 3. However, both the minimum and maximum values per course and per fraction shifted. For example, at King Hussein Cancer Centre, the maximum cost per course increased compared to baseline, reaching €10,836.35. At University Malaya Medical Centre, the minimum cost per fraction decreased to €103.62. These changes reflect shifts in cost distribution across patient and technique mixes, even though total departmental spending and average costs per course remained stable.

Table 4.21: Simulation 3: average spending-based cost per EBRT course and per fraction by centre under 80% planning time reduction. Costs include EBRT pathway activities, RO support, and non-EBRT care. Reported values reflect the average, minimum, and maximum observed across all treatment courses.

Country	**Cost per EBRT course (€)**			**Cost per EBRT fraction (€)**		
	Average	**Min**	**Max**	**Average**	**Min**	**Max**
Grote Schuur Hospital	5523.74	1024.91	8854.98	264.37	210.67	1700.58
King Hussein Cancer Centre	3286.28	349.86	10836.35	145.45	115.31	1740.10
University Malaya Medical Centre	7331.12	1553.72	44004.18	536.63	103.62	6044.44
Tata Medical Centre,Kolkata	3003.00	550.00	29115.00	174.00	85.00	1837.00

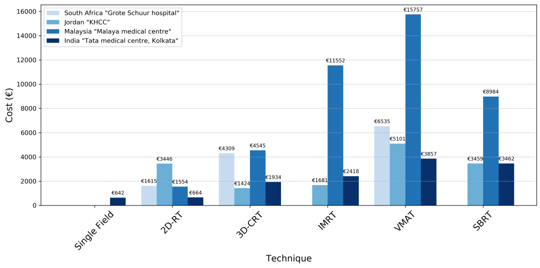
Technique-driven variation and cost drivers

Figure 4.12a shows the average spending-based EBRT cost per course by technique under Simulation 3. Across all centres, the most costly modalities were VMAT, IMRT, and SBRT, with consistently lower average costs reported for 3D-CRT, 2D-RT, and Single Field techniques. The highest average cost per course was observed for VMAT in the Malaysian centre (€15,757), followed by IMRT (€11,552) and SBRT (€8,984) in the same centre. The lowest per-course cost was reported for Single Field in the Indian centre (€642). A similar cost ranking by technique was observed across all centres, with the Indian centre consistently reporting the lowest values and the Malaysian centre the highest across modalities.

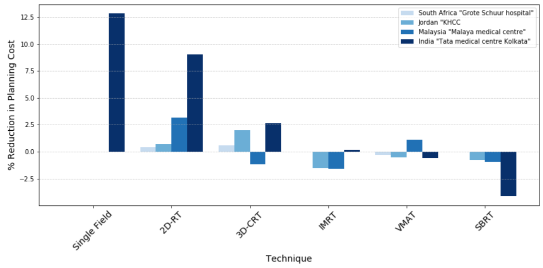
Figure 4.12b displays the percentage change in cost per EBRT course by technique, comparing Simulation 3 to baseline. Negative values indicate a reduction in cost, while positive values reflect an increase. Overall, cost reductions were most notable for higher-complexity techniques, though the magnitude varied by centre. For instance, SBRT in the Indian centre showed a reduction of 4.1%, and IMRT in the Malaysian centre declined by approximately 1.7%. In contrast, certain modalities, such as VMAT in the Malaysian centre, exhibited a slight increase in planning cost (1.0%). Among simpler techniques, 2D-RT in the Jordanian centre and Single Field in the Indian centre displayed modest increases. These changes reflect shifts in time allocation and relative resource use following department-wide planning time reduction.

Figure 4.13a presents the spending-based planning cost per EBRT course by technique under Simulation 3. Here only the EBRT-core costs are included. Across all centres, the highest planning costs were observed for VMAT and IMRT, with VMAT at University Malaya Medical Centre reaching €1,981 per course. Intermediate values were recorded for 3D-CRT and SBRT, while Single Field consistently incurred the lowest planning costs, remaining below €300 in all settings. This distribution reflects both the technical demands of each modality and the relative time required to generate clinically acceptable plans.

Across all centres and techniques, Simulation 3 resulted in an average planning cost reduction of 40.8% (SD = 4.1%) per EBRT course, as shown in Figure 4.13b. The reduction was most pronounced for 3D-CRT at University Malaya Medical Centre and King Hussein Cancer Centre, where planning costs decreased by 46% and 45%, respectively. IMRT, VMAT, and SBRT also showed substantial planning cost reductions, generally falling within a range of 38% to 45%. These consistent decreases reflect the efficiency gains achieved through automation, particularly for more complex planning



(a) Average total cost per EBRT course by treatment technique under Simulation 3. Costs include EBRT delivery, RO support, and non-EBRT departmental costs. Data are shown separately for each participating centre.



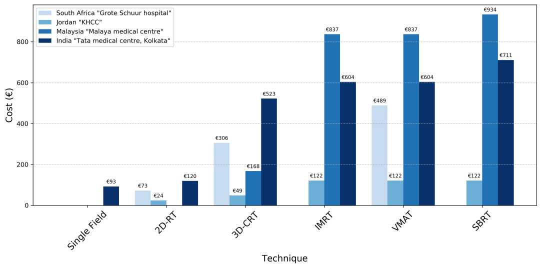
(b) Percentage change in planning-related cost per EBRT course by technique, comparing Simulation 3 to baseline. Positive values indicate increased cost, negative values indicate reduced cost.

Figure 4.12: Overview of Simulation 3 effects on EBRT course cost by treatment technique. Subfigure (a) presents absolute average costs under Simulation 3, while Subfigure (b) shows the relative change in planning-related costs compared to baseline.

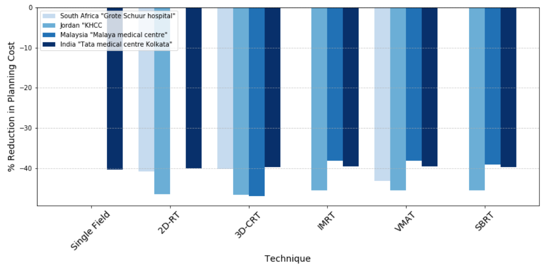
workflows.

Although the total EBRT pathway spending-based cost remained constant across Simulation 3, the internal distribution of spending-based costs among the various workflow components shifted substantially. Unlike the more uniform trends observed in resource utilisation, these cost changes were notably centre-dependent. As illustrated in Table 4.22, the equipment-related cost shares remained unchanged in the Jordanian and Malaysian centres. In contrast, the average reduction in planning-related equipment cost across all centres was 8.3% (SD = 9.8%), with considerable variation. For instance, the Jordanian centre experienced no change (0%), while the Indian centre exhibited a substantial decline of 21%. These differences can be attributed to the number of TPS available at each centre because both the Indian and South African centres were equipped with seven TPS units, whereas the Jordanian and Malaysian centres had only one. Furthermore, in both the South African and Indian centres, review and verification accounted for a larger proportion of equipment-related costs.

With respect to personnel, planning-related cost shares declined more uniformly, with an average reduction of 16.8% (SD = 6.4%). In both the Jordanian and Malaysian centres, planning dropped out of the top three personnel cost categories due to a 22% reduction, with review and verification entering the top three in Jordan and offline IGRT rising to second position. In Malaysia, treatment delivery moved into the third position,



(a) Average EBRT planning cost per treatment course by technique under Simulation 3. Costs reflect only the EBRT pathway (i.e., excluding RO support and non-EBRT activities) and are shown for each participating centre.



(b) Percentage reduction in planning cost per EBRT course by technique under Simulation 3 compared to baseline. Negative values indicate cost savings resulting from automation-related planning time reductions.

Figure 4.13: Impact of Simulation 3 on planning-related EBRT course costs across centres. Subfigure (a) shows absolute planning costs per technique, while Subfigure (b) shows the relative reduction compared to baseline.

while the remaining two components each rose by one rank.Interestingly, treatment delivery costs remained unchanged in absolute terms for both equipment and personnel across all centres. However, due to declines in planning-related costs, its relative rank shifted in some settings, such as in the Indian centre, where it surpassed planning to become the highest personnel cost component. In contrast, the South African centre exhibited only a minor change in personnel cost share, and the rank order of top cost drivers remained unchanged.

Table 4.22: Simulation 3: top three spending-based cost drivers by resource type and centre for EBRT pathway activities. Values reflect the share of total spending within each resource category (equipment and personnel).IGRT = image-guided radiotherapy; "On. IGRT & localisation" refers to online guidance and patient positioning before treatment.

Resource Type	Rank	Grote Schuur Hospital	King Hussein Cancer centre	Malaya Medical centre	Tata Medical centre, Kolkata
Equipment	1	Treatment delivery (47%)	Treatment delivery (79%)	Treatment delivery (38%)	Review & verification (33%)
	2	Review & verification (18%)	On. IGRT & localisation (7%)	On. IGRT & localisation (21%)	Planning (31%)
	3	Planning (15%)	Dosimetry (4%)	Imaging (21%)	Treatment delivery (21%)
Personnel	1	Treatment delivery (55%)	Treatment delivery (30%)	On. IGRT & localisation (26%)	Treatment delivery (16%)
	2	On. IGRT& localisation (19%)	Offline IGRT(25%)	Imaging (18%)	Planning (16%)
	3	Imaging (12%)	Review & verification (11%)	Treatment delivery (13%)	Patient assessment (12%)

5

Discussion

This thesis critically examines the potential impact of AI-based automation in RT treatment planning across four centres in LMICs. The analysis uses the ESTRO-HERO TD-ABC costing model to integrate real-world departmental data from Univesity Malaya Medical Centre (Malaysia), Tata Medical Centre, Kolkata (India) , King Hussein Cancer Centre (Jordan) and Grote Schuur Hospital (South Africa). It then simulates how the RPA could influence cost structures, workforce demands, and operational efficiency in LMIC RT settings.

The modelling process started with a detailed assessment of the current characteristics of each department, highlighting differences in planning workload, equipment constraints, and tumour-site distributions. This was followed by a series of forward-looking simulations exploring various AI integration scenarios. These scenarios reflect partial and full implementation of automated planning workflows, including minimal manual QA to ensure clinical safety.

The data confirms that, across all centres, RT is dominated by fixed costs, particularly those associated with infrastructure and salaried personnel. Consequently, even substantial reductions in planning time had a minimal impact on overall departmental spending-based costs. AI-based planning could improve workflow efficiency by reducing the burden of planning tasks and freeing up staff capacity,particularly in departments where planning accounts for a substantial share of clinical workload. However, these gains alone may not overcome downstream constraints such as shortages in treatment staff or LINAC capacity. The simulations suggest that the benefits of automation could be highly context-dependent and may be most impactful when accompanied by broader efforts to address treatment-side limitations.

These dynamics are now examined in greater detail, beginning with cross-cutting patterns related to cost, resource utilisation, and workflow efficiency, before turning to simulation-specific insights.

5.1 General discussion

Based on simulations and baseline comparisons across the four LMIC RT departments, this section summarises key patterns relating to cost, resource constraints and workflow efficiency. Despite variations in departmental structures, planning workloads, and clinical techniques across sites, three overarching themes emerged: (i) the dominance of fixed costs in departmental budgets, (ii) variation in human and equipment resource constraints, and (iii) consistent, although limited, efficiency gains enabled by AI-based planning tools. These themes influence how automation can and cannot be expected to affect the future of RT services in LMICs.

5.1.1 Cost dynamics in LMIC RT

A consistent pattern across all centres is the dominance of fixed costs within the structure of RT services. Capital equipment costs and personnel salaries accounted for between 59% and 95% of total departmental expenditure, which is consistent with previous analyses of RT cost structures in both high-income and resource-constrained settings (Spencer et al. [2021],Li and et al. [2023]). However, within such a cost profile, marginal improvements in workflow efficiency, such as those generated through the automation of contouring and plan generation, do not result in direct reductions in total spending-based expenditure. Rather, they produce internal shifts in resource allocation and capacity use.

The distinction between resource efficiency and financial impact is illustrated by comparing the Malaysian and Indian centre. Despite reporting similar total expenditures for EBRT, the Malaysia centre's lower patient throughput resulted in an average cost per course that was almost three times higher than that of the Indian centre (€7,731 vs. €2,526). This disparity does not arise from differences in pricing or staffing levels, but from the way fixed costs are distributed across varying patient volumes. In departments with relatively low throughput, fixed resources are underutilised, resulting in elevated unit costs (Subramanian et al. [2016]). These findings highlight the importance of achieving economies of scale in RT to reduce costs, particularly where capital investment has already been made. The exceptionally high maximum EBRT course cost at University Malaya Medical Centre (Table 4.9) likely reflects a combination of low patient throughput and one or more outlier cases involving highly complex planning workflows, such as head and neck SBRT. These cases require extensive personnel time and TPS use, which, when combined with the centre's high fixed costs and long reported planning times, can disproportionately inflate the per-course cost

Simulations 1 and 3 support this conclusion. Although planning time for cervical, head and neck, and prostate cases was reduced by 80%, and EBRT pathway planning costs fell by an average of 40%, the effect on total departmental expenditure was modest. Usage-based EBRT costs fell by between 2.5% and 4.6% across three centres, but spending-based costs (reflecting actual financial outlay) remained unchanged. These results reflect the fundamental constraint imposed by fixed-cost dominance: unless increased patient throughput or a reduction in staffing contracts accompanies planning efficiency, automation cannot drive budgetary savings at the departmental level (Van Dyk et al. [2017],Devicienti et al. [2010]).

Instead, AI-assisted planning could enable a redistribution of effort across the EBRT pathway. As planning time is reduced, the total time spent on the pathway decreases. This means that remaining steps,such as online IGRT and treatment delivery, constitute a larger proportion of the total workflow. Because costs are allocated proportionally based on time use in the ESTRO-HERO model, these steps appear more resource-intensive, even if their absolute time and effort remain unchanged. Rather than cost elimination, this shift reflects a reallocation of relative costs, which characterises the economic effect of AI planning tools under current structural conditions.

5.1.2 Human and physical resource utilisation

Although the cost structures of all departments were broadly similar, the distribution of human and technical resources varied considerably. These differences influenced the feasibility and impact of planning automation. One of the most notable variations was in the baseline planning workload: planning consumed a substantially larger proportion of total staff time at the Malaysian centre than at the Jordanian or Indian centres. This influenced the potential for automation to alleviate bottlenecks. In settings where planning already absorbed a significant proportion of personnel time, reductions in contouring and plan generation translated into meaningful operational relief. Where planning occupied a smaller share of clinical effort, however, the practical benefits of automation were less pronounced.

Differences in infrastructure also influenced the relevance of AI integration. Some departments, such as the Malaysian centre, were primarily constrained by limited planning systems and modest staffing shortages in the planning domain. Others, such as the Indian centre, were more constrained by treatment delivery capacity, including a substantial deficit in LINAC units and therapy radiographers. This deficit is consistent with national estimates: although India requires approximately 1,350 linear accelerators to meet demand, only 365 were operational as of 2022 (Dhankhar et al. [2021]). At the study site, this translated into the highest patient throughput across all centres, more than double that of the next busiest department, placing extreme pressure on treatment resources. In these contexts, optimising the planning process alone was insufficient to increase throughput. Therefore, while the model reports resource constraints separately for each step, it is reasonable to interpret that the effectiveness of automation depends not only on where efficiency is gained, but also on whether other components of the care pathway are sufficiently resourced to absorb and make use of the released capacity.

The South African centre presented a particular modelling anomaly. The time allocated to EBRT by clinical and physics staff was reported as only 1% and 9%, respectively , far below the levels observed at other centres. These figures reflect how responsibilities were recorded in the model, with a lot of time assigned to broader RO support and non-EBRT duties. In practice, both resource use and cost allocation likely do not reflect real clinical operations, as staff often worked beyond scheduled hours and costs were distributed proportionally based on EBRT activity. This may explain the slight increase in usage-based costs observed in Simulation 3 and suggests caution when interpreting results for this centre.

Where infrastructure was relatively sufficient but personnel were in short supply, as in the Jordanian and South African centres, automation could provide opportunities for internal task reallocation. Depending on the departmental context, reducing the time spent on planning could potentially allow staff to be redeployed to support other components of care delivery that may be under-resourced, depending on the departmental context, such as treatment delivery, QA, patient review, or adaptive planning workflows. These scenarios suggest that, even in the absence of downstream investment, planning automation may have indirect benefits, provided institutions have the flexibility to reassign staff roles. Recent qualitative research (O'Shaughnessey and Collins [2022],Hu et al. [2023],Ramiah and Mmereki [2024]) similarly notes that clinicians view AI tools as a means to improve workflow efficiency and support task redistribution rather than as mechanisms for reducing the workforce.

While the potential redistribution of planning resources was the most prominent and consistent outcome of AI implementation, other changes to workflows were also observed. Simulations indicated that, as planning time decreased, the proportion of time spent on subsequent steps, such as image guidance and treatment delivery, increased. This shift does not reflect increased activity in these domains, but rather a proportional effect: as total pathway time is reduced, the remaining steps occupy a larger share of the compressed workflow.

Taken together, these observations highlight that the value of planning automation is determined by its interaction with the broader resource profile of each department, not just by planning burden alone. Human and physical resource constraints are interdependent, and the full utility of AI integration depends on whether system bottlenecks are located within or beyond the planning domain.

5.2 Specific observations

Figures 4.2,4.3, 4.6a, 4.11a) and Tables 4.12, 4.17 display estimated surpluses or deficits of equipment and personnel relative to EBRT pathway demands. It is important to interpret these figures and tables with appropriate caution. While these figures are useful for identifying potential bottlenecks in care delivery, not all observed shortfalls should be interpreted as requiring immediate investment. For instance, a deficit of –0.2 full-capacity units does not necessarily justify the acquisition of a new LINAC or the hiring of an additional full-time staff member, given the substantial fixed costs associated with such investments. Economic efficiency would typically favour action only when deficits approach or exceed one full-capacity unit, or when smaller shortfalls are sustained and systemically limiting throughput. Nonetheless, these modelled values provide valuable insight into resource pressure points and should be viewed as indicative of areas where workflow strain may exist, rather than as direct investment triggers.

5.2.1 Simulation 1

Simulation 1 was designed to prospectively estimate the expected impact of the RPA on the secondary outcome of the ARCHERY study: changes in planning time and resource use. It focused on cervical, head and neck and prostate cancers , applying planning time reductions of 70%, 80% and 90% for these tumour types to simulate the expected AI-driven gains. Although these tumour types were clinically important, they represented only a modest proportion of the overall EBRT workload across centres.

Consequently, while the measurable gains were operationally relevant, they had a limited overall impact. Consistent declines in planning resource use were observed across centres. On average, demand for planning personnel fell by 0.9 FTE, TPS utilisation dropped by 0.3 units and the planning share of EBRT activity decreased by 5.2% for equipment and 5.9% for personnel. These figures confirm that AI-assisted planning can alleviate the strain on digital infrastructure and clinical staff, even when applied to a subset of cases.

However, the scale of these reductions was insufficient to produce structural change. In Univeristy Malaya Medical Centre, where a single TPS was used and planning accounted for nearly one-third of staff time, efficiency gains helped to relieve local pressure, but did not alter departmental throughput or cost structure. In centres such as Grote Schuur Hospital, baseline staffing deficits persisted despite the simulation. In Tata Medical Centre,Kolkata , meanwhile, delivery remained the dominant constraint, with 3.1 LINACs and over 15 FTEs missing from treatment delivery. Interestingly, no change in TPS demand was observed at King Hussein Cancer Centre. This outcome likely reflects the atypical patient population at the site, which had considerably lower volumes of cervical, head and neck, and prostate cancer cases which are the specific tumour types included in the simulation. As a result, the planning time reductions modelled in Simulation 1 had minimal effect on overall system workload. These outcomes reinforce the fact that efficiency gains have little systemic value unless they address a department's primary bottleneck.

This reflects the distinction between reducing workload and addressing resource constraints. A 5-6% shift in time allocation could make day-to-day operations easier like improving scheduling flexibility, reducing burnout, or allowing staff to reallocate time to QA, but it is unlikely to unlock additional treatment volume unless coupled with broader structural changes. This means that in the case of ARCHERY, it could offer efficiency, not capacity; the value lies in streamlining a constrained process, not replacing the skilled workforce that enables it.

The planning-specific cost per course for the three tumour types decreased significantly, with an average reduction of 41.5% (SD = 4.2%). These figures reflect the modelled 80% planning time reduction and align with prior expectations that high-complexity workflows, such as those required for VMAT or head and neck cases, benefit most from automation. However, due to the current lack of detailed costing studies at a technical level in RT, especially in the context of AI tools, it remains difficult to fully situate these findings within the existing literature.

In the four centres, usage-based EBRT costs fell modestly by between 0.7% and 3.6%. However, spending-based departmental costs, reflecting actual budget outlays, remained unchanged. This is consistent with the structural dominance of fixed costs in LMIC RT. The absence of change in this model reinforces the distinction between efficiency and expenditure: ARCHERY can reduce how resources are deployed, but not necessarily how much is paid—at least in the short term. Still, the simulation demonstrates that departments may have latent cost capacity to treat more patients within existing budgets, provided that other constraints (such as LINAC or treatment staff shortages) do not limit throughput.

Finally, Simulation 1 exposed a methodological limitation when interpreting planning costs at the technique level. As demonstrated in Figure 4.8, the mean cost per EBRT course for $Stereo\_archery$ (SBRT) increased at both the Malaysian and Indian centres under the simulation, despite an 80% reduction in planning time. A similar pattern is seen for $3D\_archery$ at the Malaysian centre, where costs increased by more than 100% compared to the baseline. This seemingly paradoxical result is attributable to the manner in which tumour types were reallocated during the simulation, with only cervical, head and neck, and prostate cancer cases being designated as "$\_archery$" technique categories. These tumour types often necessitate more intensive planning requirements, such as detailed contouring, stricter dose constraints, or more comprehensive QA, in comparison to the broader population of patients treated with SBRT or 3D-CRT. Consequently, the "$\_archery$" technique groups represent a higher-effort subset of patients, which results in the average cost per course within those categories being inflated, despite the application of time savings. This underscores the necessity of exercising caution when interpreting technique-level cost fluctuations in partial-scope simulations, where alterations in case composition can result in the distortion of apparent cost trends.

Notably, tumour-type-specific results revealed variation in the magnitude of cost reductions under Simulation 1 (Figure 4.9), further emphasizing the importance of baseline clinical complexity and departmental context. Cost savings were most substantial for cervical and head and neck cancers, which typically require more intensive contouring and planning. This was particularly evident in centres with higher baseline planning effort, such as Tata Medical Centre and University Malaya Medical Centre. In contrast, centres with lower volumes of ARCHERY tumour types or more limited planning intensity, such as King Hussein Cancer Centre, experienced little or no change. These findings suggest that AI planning tools may be especially impactful for high-complexity tumour sites, where manual planning is most resource-intensive.

The sensitivity analysis conducted across 70%, 80%, and 90% planning time reduction scenarios in Simulation 1 confirmed that the majority of the operational and cost-related benefits of automation are achieved in the early stages, with diminishing returns at higher levels of time savings. Across all centres, the top-ranked equipment and personnel tasks demonstrated stability, with shifts in time allocation being minimal, typically less than 1% between scenarios. As demonstrated in the results, usage-based costs and planning-related FTEs exhibited only marginal improvements between the scenarios. The findings indicate that while initial planning automation offers discernible efficiency gains, further reductions beyond a certain threshold yield limited additional value, thereby reinforcing the robustness and saturation effect of partial AI implementation.

In summary, Simulation 1 showed that partial AI planning can act as a tactical tool, providing targeted support to departments with recognised planning bottlenecks. The intervention was most effective in centres with a high planning burden and minimal delivery constraints. Although it did not deliver broader capacity expansion or cost reduction, it did provide operational resilience, which is a valuable strategic outcome in LMIC settings where even modest gains can enhance service stability and reduce vulnerability to staffing or equipment strain. For departments considering initial AI implementation, these findings suggest that narrow deployment may offer worthwhile benefits, especially when aligned with specific departmental constraints and patient mix.

5.2.2 Simulation 2

Simulation 2 introduced a brief, 10-minute manual plan check to reflect the likely clinical implementation of AI-based planning tools, where quality validation remains essential despite workflow automation. The addition of this QA step had no measurable impact on departmental resource use, equipment requirements or overall costs. This is consistent with recent findings by De Kerf et al. [2025], whose multicentre FMEA identified manual review as the most risky step in automated workflows, due to the challenges of human oversight, skill degradation, and protocol adherence rather than technical limitations. These findings underscore the need for QA to accompany the use of AI, not as a barrier, but as an integrated safeguard. Indeed, numerous studies reinforce the ethical and clinical responsibility to validate AI-generated treatment plans, particularly as regulatory and safety expectations evolve (Brouwer et al. [2020],Neylon et al. [2023]).While some have raised concerns that such oversight may be resource-intensive or disruptive (Dewhurst et al. [2015],Liu et al. [2019]), our findings suggest the opposite: when well designed, a lightweight QA step can be operationally absorbed with minimal burden. This is particularly relevant in LMIC settings, where resources are constrained but patient safety must remain paramount. Simulation 2 therefore provides reassuring evidence that quality checks can be integrated into AI planning workflows without compromising implementation feasibility or efficiency.

5.2.3 Simulation 3

Simulation 3 extended AI-based planning to the entire EBRT pathway, amplifying the effects observed in Simulation 1. It confirms consistent trends. While the direction of change remained consistent - reduced planning time, reduced FTE and TPS requirements, and reduced planning-specific costs - the broader application provides a clearer insight into where planning automation could enable structural change and where its value remains limited.

The most significant improvements were in planning resource use, with planning FTE requirements reduced by an average of 2.6 FTE per centre and TPS requirements reduced by an average of 0.8 units across all centres. However, as in previous simulations, these gains did not translate uniformly into increased capacity. At the Indian centre, where LINAC and treatment staff shortages persisted, the modelling results suggest that improvements in planning efficiency alone were unlikely to translate into increased throughput. This supports the broader inference that efficiency gains in one part of the care pathway may have limited impact unless other system components are adequately resourced to absorb the additional capacity.

That said, Simulation 3 shows where strategic value can be unlocked. In departments with only staff shortages, such as Grote Schuur Hospital and King Hussein Cancer Centre, where infrastructure is available but staffing limits throughput, the freed up planning FTE could potentially be reallocated to alleviate delivery bottlenecks. While this depends on institutional flexibility and staff training, it suggests that AI planning could support not only workflow streamlining but also internal task-shifting, helping departments to address broader resource gaps without increasing overall staffing levels.

In terms of costs, Simulation 3 again confirmed that overall departmental expenditure remains unaffected due to the fixed cost nature of RT. However, there was a significant shift in the internal distribution of EBRT costs. On average, the share attributed to treatment planning activities, including contouring, decreased by 27.2% for equipment and 12.3% for personnel. The average planning-related cost per EBRT course also dropped by over 40%. While these do not represent overall savings at departmental level, they do indicate a structural rebalancing that could enable departments to reallocate freed-up planning capacity towards improving quality, handling more complex cases, or increasing patient throughput — provided that other system constraints allow it.

In summary, simulation 3 illustrates that while full automation of planning increases efficiency, its transformational impact depends on the system context. Where capacity exists and constraints are limited to staff, AI planning can help alleviate bottlenecks through strategic reallocation. Where equipment is the binding constraint, gains remain in workforce pressure alleviation. Full implementation, while not sufficient on its own, becomes a powerful enabler, particularly in environments able to translate planning efficiency into broader system performance.

5.3 Limitations

Several limitations should be acknowledged when interpreting the findings of this study. First, while the ESTRO-HERO model is well-established and validated for assessing RT services across Europe, it was not originally designed to evaluate the impact of highly specific innovations such as AI-assisted planning. Its general-purpose structure makes it less suited to capturing the nuanced and evolving workflows associated with AI integration.

Another limitation of this study is the restricted scope of the sensitivity analysis. While Simulation 1 explored planning time reductions of 70%, 80%, and 90%, additional scenarios, such as 50% or 60% reductions, could have provided a more comprehensive understanding of the relationship between time savings and resource or cost outcomes. Moreover, sensitivity analysis was not extended to Simulations 2 and 3, where applying a similar range of planning time reductions could have strengthened the robustness of findings and offered further insights into the scalability and generalisability of AI-driven efficiency gains across broader implementation scenarios.

A central constraint is that the model does not distinguish between the individual processes of autocontouring and autoplanning, instead aggregating the entire planning phase into a single time estimate. This limits the ability to accurately reflect the step-specific efficiency gains offered by tools like the RPA, for which the ARCHERY study collected disaggregated timing data. In addition, the model assigns timing values based on treatment technique alone, without accounting for tumour site. In clinical practice, the time spent on simulation, contouring, planning, and QA differs substantially between tumour types, but the model applies uniform durations across all cases using the same technique (e.g., IMRT), which limits the granularity and tumour-specific relevance of the cost estimates. While a workaround was implemented by grouping ARCHERY tumour sites under broader technique categories, this simplification still failed to fully capture the site-specific variability reported in clinical literature and practice.

Another limitation relates to data consistency. The accuracy of the model outputs depends heavily on how uniformly the participating centres interpreted and completed the costing tool. For example, differences in how TPS systems were reported, whether as software licenses, physical machines, or workstations, may have led to inconsistencies in resource allocation and cost calculations. Another illustrative example is the reported planning time for the Malaysian centre. While the study of Hizam et al. [2019] indicates that over 50% of Malaysian RT departments report planning times exceeding eight hours, the duration observed in this study remains exceptionally high. This raises questions about the underlying cause, such as whether the extended duration reflects continuous software processing time or sustained active engagement by planning personnel.

This limitation applies to both the present simulation study and the broader ARCHERY study, from which its parameters are derived. All participating centres are located in middle-income countries (MICs), with no representation from low-income countries. The selected sites are also academic institutions with an existing infrastructure for oncology research, and several of them were involved in the co-development or preliminary testing of RPA. While this ensures feasibility and high-quality data input, it limits the generalisability of the findings to the wider LMIC context. Many low-income countries, and even some less-resourced MICs, lack the digital infrastructure, staffing or institutional readiness required to implement AI planning tools. Consequently, the efficiency and cost gains observed in this study may be more than can currently be achieved in more constrained settings where the conditions necessary for integrating AI remain unmet.

Furthermore, a context-specific limitation is the absence of data on waiting times or cancer stage at diagnosis. In many LMICs, long delays in access to RT contribute to patients presenting with more advanced-stage cancers, which require more complex treatment and carry worse prognoses. Because this study did not collect or model data on waiting times, it was not possible to assess whether the implementation of AI-based planning tools like ARCHERY might reduce delays and thereby impact stage at treatment initiation. This represents an important blind spot, particularly given that timeliness of care is a critical determinant of outcome in resource-limited settings.

In addition, it is possible that residual effects of the COVID-19 pandemic may have influenced some of the data collected in 2022, particularly in terms of staff availability or workflow disruption (Henley et al. [2022],Li et al. [2023]). While the modelled simulations abstract from short-term variability, any pandemic-related distortions in planning time or resource utilisation may affect how representative the baseline estimates are of typical departmental operations. However, as this study models the potential efficiency gains of AI planning tools rather than real-time clinical performance, the impact of such disruptions is likely to be limited.

Finally, this thesis did not consider the costs associated with implementing the AI tools themselves. The analysis focused on the downstream resource and cost implications of deploying an AI tool such as RPA, but did not include estimates for acquisition, training, integration or ongoing maintenance. In LMIC contexts, where budget constraints are particularly acute, these costs can be a significant barrier to adoption. Future economic evaluations should include these real-world expenditures to better assess the overall affordability and scalability of AI-assisted RT planning.

These limitations underscore both the adaptability and the boundaries of applying a standardised costing model to evaluate a complex, workflow-altering intervention like AI planning within the diverse realities of LMIC RT services.

5.4 Future work

This study used the ESTRO-HERO model to provide simulation-based estimates of the impact of AI-assisted planning in RT departments, offering valuable insights into cost and resource dynamics. However, several important areas remain open for further research.

Firstly, since the ARCHERY study is ongoing, future analyses should incorporate real-world RPA planning times, to directly compare modeled projections with observed outcomes. This validation is essential to refine the assumptions and expectations regarding the efficiency gains achievable through AI planning automation.

Secondly, future research should extend beyond simulations to evaluate AI planning tools in routine clinical practice. Assessing whether AI-driven efficiencies meaningfully reduce treatment delays, affect plan acceptance rates, or facilitate earlier initiation of treatment will be particularly crucial in LMIC settings. In these regions, long waiting times often contribute to patients presenting with more advanced disease, highlighting the importance of timely access to RT. Evaluating real-world effectiveness in reducing delays would thus provide critical insights into the true clinical value of AI integration.

To enhance clinical outcome evaluations, future studies should explicitly link TD-ABC methodologies to value-based healthcare frameworks, thereby connecting cost efficiency directly to patient outcomes and care quality metrics. This integration would significantly enhance economic evaluations, making them more directly useful for policymakers and supporting more effective resource allocation.

Additionally, future research should broaden geographic representation by including lower-income countries, where infrastructure constraints, economic barriers, and workforce shortages may significantly influence AI implementation and effectiveness. Assessing AI planning tools in such constrained environments would enhance the generalizability and global relevance of findings, providing practical insights into how AI could realistically address global inequities in RT access.

Moreover, establishing standardized costing methodologies and reporting practices remains crucial. Variability in data interpretation and reporting among centres, as observed in this study, complicates cross-centre comparisons. Clear, internationally accepted costing standards would facilitate more robust and comparable economic evaluations, strengthening evidence-based policymaking and investment planning.

Finally, comprehensive economic evaluations incorporating both implementation costs and long-term resource implications should be prioritized. Given the persistent shortage of high-quality costing data in RT, especially in LMIC contexts, such detailed analyses are essential to assess the real-world affordability and scalability of AI-assisted planning. Alongside economic considerations, future studies should also investigate long-term clinical outcomes, including patient survival, treatment toxicity, and quality-of-life indicators. This broader approach would provide a comprehensive assessment of whether improvements in planning efficiency ultimately translate into measurable patient benefits and sustainable healthcare improvements.

6

Conclusion

This thesis evaluated the impact of AI-based treatment planning on the cost structure and utilisation of resources for RT services in LMICs, using the ESTRO-HERO TD-ABC model. Baseline costing data derived from the ARCHERY study were used to simulate the introduction of the RPA and quantify the potential operational and financial consequences for cervical, head and neck, and prostate cancer pathways. Additional simulations extended this analysis to a hypothetical future scenario in which RPA planning is applied to all tumour types.

Although planning time reductions of up to 80% were assumed for selected tumour sites based on the available literature, the results indicate that the overall effect on departmental spending remains modest. This is primarily due to the predominance of fixed costs, particularly those related to equipment and personnel, which together account for the majority of expenditure in EBRT. Consequently, while notable improvements in workflow efficiency were simulated, these did not translate into substantial financial savings under current cost structures based on spending. Changes were more evident in the usage-based cost view, though these were still limited by the inflexibility of fixed capital resources.

Nevertheless, implementing automated planning could enable some reallocation of personnel time, particularly within the treatment planning team. In departments where workforce shortages are the main constraint, this could help to alleviate specific bottlenecks. However, any increase in patient throughput is dependent on sufficient capacity being available at all stages of the EBRT workflow, including imaging, QA, and treatment delivery. As each step must be capable of absorbing an increased volume, upscaling is only feasible if there are no limiting factors elsewhere in the system. In simulations calibrated to reflect the actual service delivery conditions of the ARCHERY study sites, alleviating resource constraints had only a modest impact. These findings emphasise the importance of considering AI implementation in the context of a department's broader infrastructure and operational limitations, and caution against overestimating the standalone impact of planning automation on throughput.

The thesis also draws attention to the methodological challenges in conducting standardised economic evaluations in RT. Variations in data availability, modelling assumptions and costing methodologies complicate cross-site comparisons, reinforcing the need for consistent and transparent approaches to economic modelling.

In conclusion, while AI-based planning does not substantially alter the cost dynamics of RT departments in LMICs under fixed-cost conditions, it may offer meaningful operational improvements, particularly with regard to personnel utilisation, that contribute to incremental capacity gains. Future research should incorporate these findings into dynamic models of departmental throughput and service delivery, taking into account outcome data and system-level constraints, in order to assess the value of AI-driven RT planning more fully.

7

Societal Reflection

The integration of AI into RT planning is part of a wider shift in healthcare towards digital transformation. As AI-driven tools become more prevalent in supporting clinical decision-making and automating workflows, their application in oncology gives rise to significant societal, ethical and policy considerations, particularly in LMICs, where limited resources are an ongoing challenge.

7.1 AI and digital health transformation

AI is playing an increasingly important role in transforming healthcare systems, primarily by automating complex tasks and supporting clinical workflows. In RT, for example, treatment planning is time-consuming and requires highly skilled staff. AI offers a promising solution to workforce shortages, particularly in LMICs, where such expertise is scarce.

Automated tools such as the RPA can help to streamline processes and redistribute staff effort. However, this thesis demonstrates that these benefits are neither automatic nor system-wide. RT involves multiple interdependent steps, so reducing planning time does not necessarily lead to higher throughput if other stages, such as imaging, machine availability or treatment delivery, remain bottlenecks. AI can only add value when the entire clinical pathway is ready to absorb efficiency gains.

Furthermore, implementing AI in LMICs necessitates careful consideration of digital infrastructure, workforce training, and local clinical conditions. Most AI tools are developed in high-income contexts and may not perform reliably in different environments without proper validation and adaptation.

In short, while AI has the potential to support more efficient and equitable care, particularly in under-resourced settings, its benefits depend on thoughtful and context-sensitive integration. Technology alone is not the answer, it must fit into broader strategies for strengthening the health system.

7.2 Contribution to the Sustainable Development Goals

This work most directly aligns with Sustainable Development Goal (SDG) 3: Good Health and Well-being.

Target 3.4 aims to reduce premature mortality from non-communicable diseases (NCDs), such as cancer, by improving access to and the quality of treatment. Enhancing the efficiency of RT through AI could improve access to timely treatment in LMICs, where services are often limited despite rising cancer incidence. Furthermore, AI-based planning has the potential to standardise and, in some cases, improve the quality of treatment planning, particularly in settings with a lack of experienced staff. This could lead to more consistent care and, ultimately, improved treatment outcomes.

It also supports Target 3.c, which calls for increased health financing and the strengthening of the health workforce in developing countries. AI-based planning tools can ease the burden on scarce treatment planning staff, enabling better use of limited personnel and potentially contributing to more sustainable workforce models. While these tools cannot replace trained professionals, they can provide valuable support to improve task allocation, reduce burnout and create capacity for training and retention efforts.

7.3 Ethical and regulatory considerations

The use of AI in healthcare raises critical ethical and regulatory challenges concerning transparency, accountability and equity. Although this thesis did not involve patient-level data, it evaluated the potential implementation of an AI-based RT planning tool originally developed in a high-income setting, but co-developed and tested in collaboration with LMIC centres. This cross-context design makes issues of validation and adaptation especially relevant when considering broader deployment. Cross-context applications such as this demand close scrutiny, as variations in imaging protocols, disease patterns and clinical infrastructure can compromise performance and safety without rigorous validation.

From a regulatory standpoint, the EU Artificial Intelligence Act classifies RT planning tools as ’high-risk’ systems. This means that, if tools such as the RPA are to be adopted in clinical practice, they must comply with transparency, human oversight, risk management and post-market surveillance requirements. These obligations are directly relevant to the kind of tool explored in this thesis, especially as its deployment would cross national borders and healthcare systems.

Additionally, while this research did not involve identifiable patient data, the real-world implementation or future evaluation of such systems would need to comply with the General Data Protection Regulation (GDPR), particularly with regard to training or validating models using clinical datasets. The GDPR imposes strict conditions on data use, including lawful processing, data minimisation and the right to meaningful information about automated decisions, all of which apply to AI in healthcare.

In LMICs, where regulatory frameworks for AI may be limited or still evolving, these concerns become even more pressing. Adoption must be accompanied by local oversight, accountability mechanisms, and adaptation to regional clinical realities. The findings of this thesis reinforce the idea that, while AI can support clinical efficiency, its ethical and regulatory implications must not be overlooked.

AI-driven solutions in RT planning show promise in addressing global health inequities. However, their real-world impact depends on how well they are integrated into the broader healthcare system, taking into account limitations in infrastructure, workforce dynamics and regulatory safeguards. This work emphasises that technology alone is not the solution, but rather a tool that must be deployed thoughtfully in order to support equitable and effective cancer care.

8

Documentation use generative AI

In the development of this thesis, generative AI tools (specifically ChatGPT) were used in a transparent and responsible manner to support various aspects of the research and writing process. All outputs generated by the AI were critically reviewed, verified, and adapted by the author. The final responsibility for the content remains entirely with the author of this thesis. The following outlines how generative AI was used during this project:

- Writing assistance and improvement of writing style: ChatGPT was used to help structure and refine several sections of the thesis, including the theoretical framework, methodology, and discussion of results. The tool provided suggestions for clearer wording and organization, which were then reviewed and edited to align with academic standards and the author's voice.
- Grammar and spelling checks: Generative AI was used to support proofreading by identifying and correcting grammatical and spelling errors in both English and Dutch sections of the thesis.
- Summarizing texts: AI tools were employed to generate concise summaries of complex academic papers and reports, helping to more efficiently extract and interpret key ideas during the literature review.

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Appendices

Attachment A : screenshots of the data entry interface

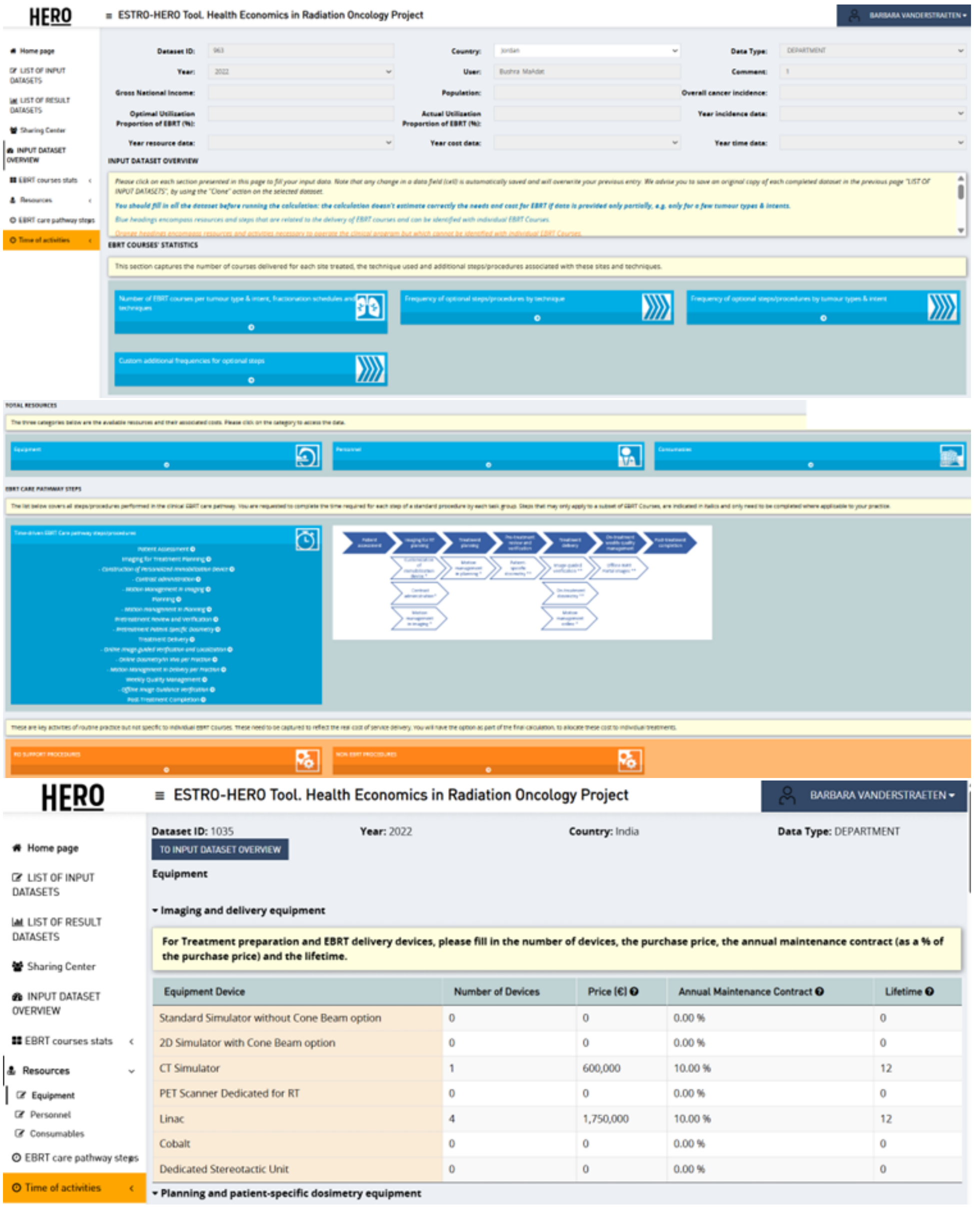

Figure 1: Screenshots of the data entry interface used in the ESTRO-HERO TDABC model. The images illustrate the standardized structure through which participating centres recorded equipment, personnel, and workflow data for simulation and cost modelling.

Attachment B: Baseline model outputs

This appendix presents detailed outputs from the baseline ESTRO-HERO TDABC models for all four centres. The data are organized into three main areas: departmental characteristics, resource utilization, and cost breakdowns. The cost section includes full results based on the usage-based costing approach, as applied in the ESTRO-HERO model. These tables support the figures presented in Chapter 4.

.0.1 Departmental characteristics

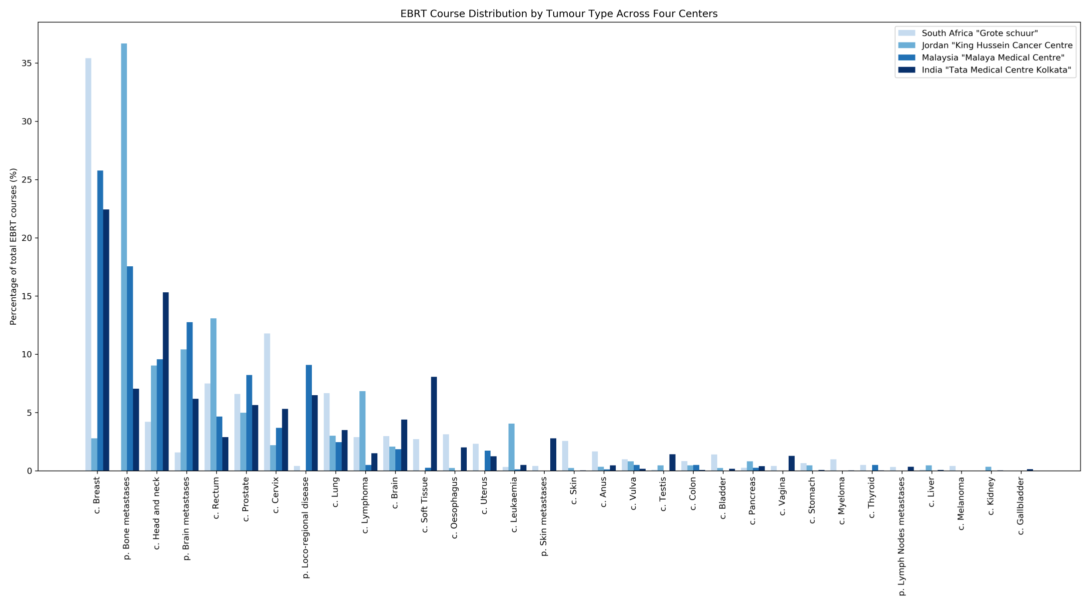

Figure 2: Full distribution of tumour sites treated with EBRT across the four study centres.

.0.2 Resource utilization

Table 1: Top three equipment time drivers at each centre under 70 % and 90 % planning-time-reduction scenarios of Simulation 1. Values denote the share of total equipment time allocated to each task; IGRT = image-guided radiotherapy (online set-up verification and localisation).

Scenario	**Rank**	Grote schuur Hospital	King Hussein Cancer Centre	Malaya Medical Centre	Tata Medical Centre, Kolkata
70 % reduction	1	Treatment delivery (39.54%)	Treatment delivery (49.14%)	Planning (47.33%)	Treatment delivery (38.14%)
	2	Planning (33.54%)	Planning (27.48%)	Treatment delivery (24.38%)	Planning (27.26%)
	3	On. IGRT & localisation (11.89%)	Review & verification (5.83%)	On. IGRT & localisation (13.53%)	On. IGRT & localisation (14.51%)
90 % reduction	1	Treatment delivery (40.46%)	Treatment delivery (49.57%)	Planning (43.75%)	Treatment delivery (39.00%)
	2	Planning (31.98%)	Planning (26.84%)	Treatment delivery (26.04%)	Planning (25.63%)
	3	On. IGRT & localisation (12.17%)	Review & verification (5.88%)	On. IGRT & localisation (14.45%)	On. IGRT & localisation (14.84%)

Table 2: Top three personnel time drivers at each centre under 70 % and 90 % planning-time-reduction scenarios of Simulation 1. Values denote the share of total personnel time allocated to each task; IGRT = image-guided radiotherapy (online set-up verification and localisation).

Scenario	**Rank**	Groote schuur Hospital	King Hussein Cancer Centre	Malaya Medical Centre	Tata Medical Centre, Kolkata
70 % reduction	1	Treatment delivery (57.20%)	Treatment delivery (65.22%)	Treatment delivery (34.92%)	Treatment delivery (43.33%)
	2	On. IGRT & localisation (14.16%)	Planning (9.12%)	Planning (22.60%)	On. IGRT & localisation (16.49%)
	3	Planning (9.99%)	On. IGRT & localisation (5.76%)	On. IGRT & localisation (21.04%)	Planning (10.32%)
90 % reduction	1	Treatment delivery (57.59%)	Treatment delivery (65.40%)	Treatment delivery (36.01%)	Treatment delivery (43.69%)
	2	On. IGRT & localisation (14.62%)	Planning (8.85%)	Planning (21.70%)	On. IGRT & localisation (16.62%)
	3	Planning (9.37%)	On. IGRT & localisation (5.77%)	On. IGRT & localisation (20.17%)	Planning (9.57%)

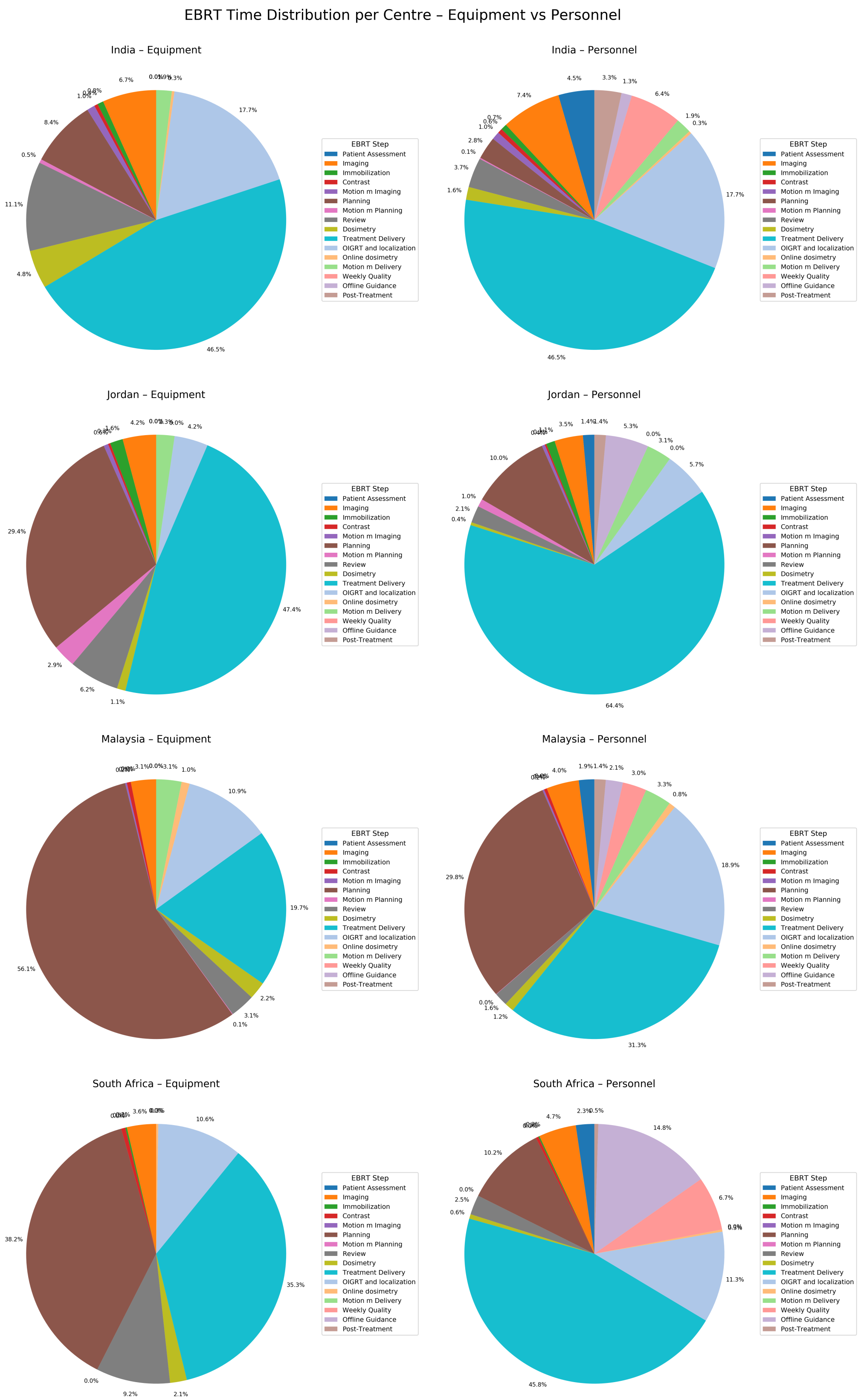

Figure 3: Full distribution of time-share allocations for both equipment and personnel across EBRT steps for all centra

.0.3 Cost breakdown

Table 3: Total annual usage-based departmental costs by centre, with breakdown of expenditures across major cost categories (incl. EBRT, RO Support and Non-EBRT cost).

Resource	Grote schuur Hospital	King Hussein Cancer Centre	Malaya Medical Centre	Tata Medical Centre, Kolkata
Total (€)	6,338,165.77 (100%)	2,839,770.25 (100%)	3,965,629.11 (100%)	5,079,846.02 (100%)
EBRT care pathway steps (€)	3,573,135.93 (56.4%)	2,684,145.26 (94.5%)	2,850,537.69 (71.9%)	4,095,930.16 (80.6%)
Equipment (€)	1,974,314.86 (31.1%)	2,395,603.25 (84.4%)	2,557,883.81 (64.5%)	3,435,681.67 (67.6%)
Personnel (€)	1,577,554.18 (24.9%)	167,835.34 (5.9%)	289,005.77 (7.3%)	603,917.73 (11.9%)
Consumables (€)	21,266.88 (0.3%)	120,706.68 (4.3%)	3,648.11 (0.1%)	56,330.76 (1.1%)
RO Support (€)	2,959,819.22 (28.1%)	113,236.12 (4.0%)	524,869.25 (13.2%)	798,713.27 (15.7%)
Non-EBRT Care (€)	986,968.69 (15.6%)	42,388.85 (1.5%)	590,222.17 (14.9%)	185,202.60 (3.6%)

Table 4: Average cost per EBRT course and per fraction by centre, based on total usage-based departmental expenditures. Costs include EBRT pathway activities, RO-support, and non-EBRT care. Reported values reflect the average, minimum, and maximum observed across all treatment courses.

Country	**Cost per EBRT course (€)**			**Cost per EBRT fraction (€)**		
	Average	**Min**	**Max**	**Average**	**Min**	**Max**
Grote Schuur Hospital	5,220.92	906.64	8,805.36	249.89	187.60	1,392.54
King Hussein Cancer Centre	3,813.04	245.03	13,412.48	169.03	141.52	1,581.56
University Malaya Medical Centre	7,730.95	705.14	32,460.53	536.62	98.73	2,391.59
Tata Medical Centre, Kolkata	2,526.00	233.00	23,030.00	146.00	69.00	1,151.00

Table 5: Top three usage-based cost drivers by resource type and centre for EBRT pathway activities. Values reflect the share of total spending within each resource category (equipment and personnel).IGRT = image-guided radiotherapy; "On. IGRT & localisation" refers to online guidance and patient positioning before treatment.

Resource type	Rank	Grote schuur Hospital	King Hussein Cancer Centre	Malaya Medical Centre	Tata Medical Centre, Kolkata
Equipment	1	Treatment delivery (53%)	Treatment delivery (87%)	Treatment delivery (59%)	Treatment delivery (56%)
	2	Planning (24%)	On. IGRT & localisation (8%)	On. IGRT & localisation (29%)	On. IGRT & localisation (29%)
	3	On. IGRT & localisation (16%)	Motion management delivery (4%)	Motion management delivery (8%)	Planning (15%)
Personnel	1	Treatment delivery (37%)	Treatment delivery (63%)	Planning (40%)	Treatment delivery (44%)
	2	Offline IGRT (29%)	Planning (13%)	Treatment delivery (29%)	On. IGRT & localisation (36%)
	3	Planning (19%)	On. IGRT & localisation (6%)	On. IGRT & localisation (19%)	Planning (13%)

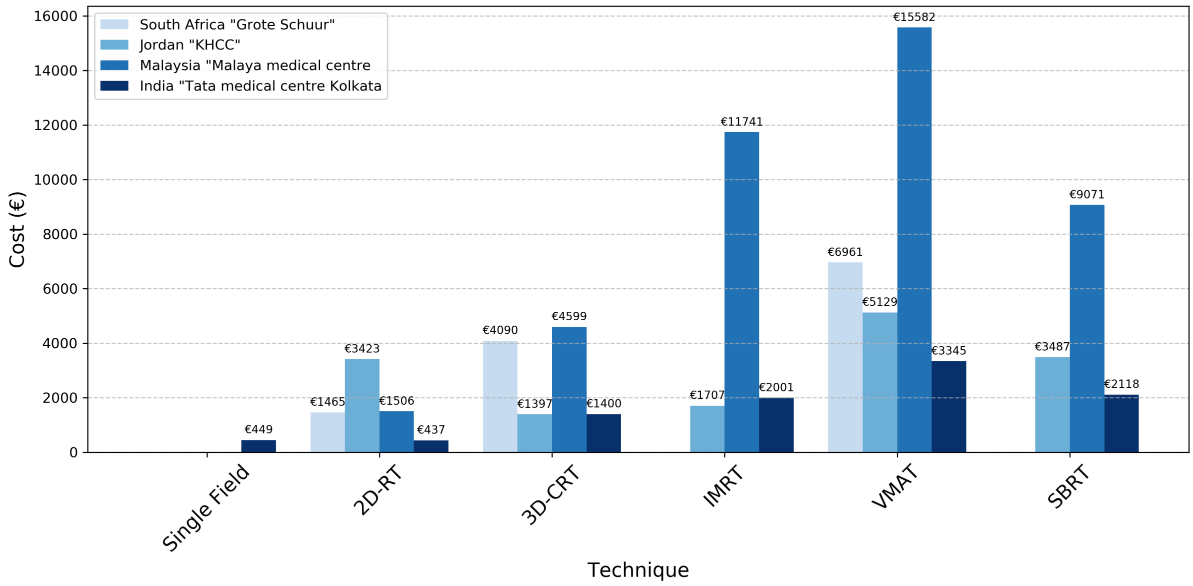

Figure 4: Average usage-based cost per EBRT course by RT technique and centre. Costs include EBRT care pathway activities, RO support, and non-EBRT care. Bars represent the average total cost per course for each technique at the four centres.

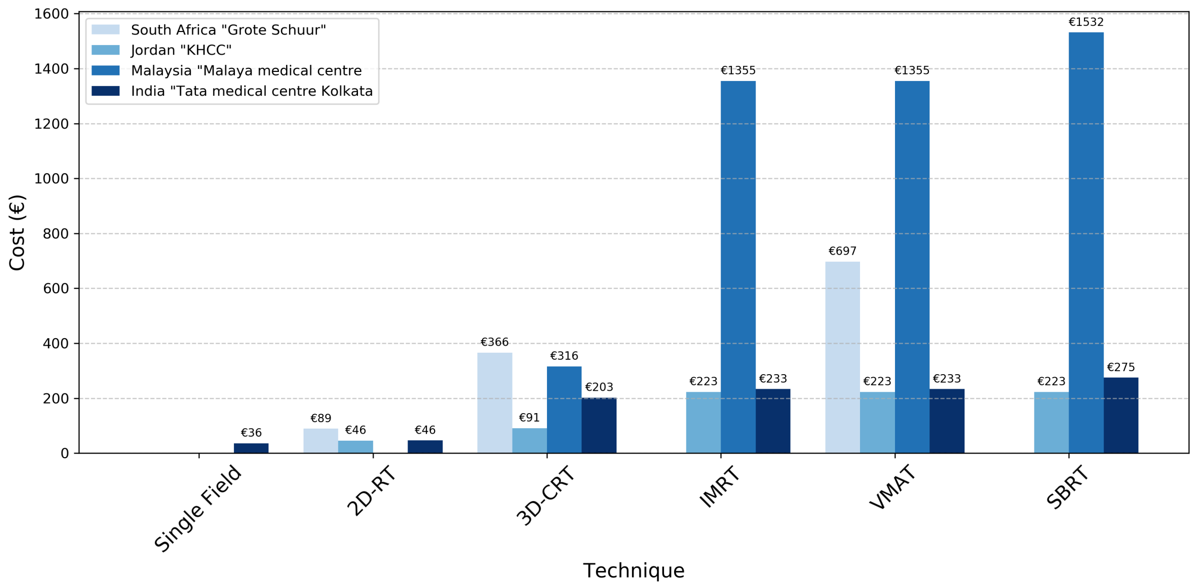

Figure 5: Average EBRT usage-based planning cost within the EBRT care pathway per course by technique and centre. Missing bars indicate that the technique was not in clinical use at the respective centre. Costs exclude RO-support and non-EBRT care.