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Clinical adoption of radiobiological models and artificial intelligence in radiotherapy treatment planning: a cross-sectional practice survey

Kalyan Mondal[1,2a], **Abhijit Mandal**[3b] and **Anuj Vijay**[1c]

[1]Department of Physics, Institute of Applied Science & Humanities, GLA University, Mathura 281406, Uttar Pradesh, India
[2]Department of Radiation Oncology, North Bengal Medical College & Hospital, Darjeeling 734012, West Bengal, India
[3]Department of Radiotherapy and Radiation Medicine, Institute of Medical Sciences, Banaras Hindu University, Varanasi 221005, Uttar Pradesh, India
[a]https://orcid.org/0000-0001-7685-7391
[b]https://orcid.org/0000-0001-5626-1072
[c]https://orcid.org/0000-0001-6610-3844

Abstract

Introduction: Radiobiological models optimising tumour control probability (TCP) and normal tissue complication probability (NTCP) underpin effective radiotherapy treatment planning; however, real-world adoption – particularly in low- and middle-income country (LMIC) settings and for plan evaluation – remains poorly characterised alongside emerging artificial intelligence and machine learning (AI/ML) applications.

Methods: This cross-sectional survey is a pre-specified component of a mixed-methods systematic review registered with PROSPERO (CRD420251146188); the survey itself is not separately registered. A 40-item anonymous instrument was distributed via the MEDPHYS mailing list and professional society channels. Forty-two self-selected professionals from 10 countries (India 71.4%) responded. Analysis was descriptive, with Wilson 95% confidence intervals; proportions are reported on the full sample (N = 42), with the number of non-respondents stated for every item. Reporting follows CHERRIES guidelines for internet e-surveys.

Results: Confirmed local calibration of radiobiological model parameters was reported by 14.3% (95% CI 6.7%–27.8%) of respondents; 40.5% (95% CI 27.0%–55.5%) reported no calibration and a further 40.5% did not know their institution's calibration status. Biologically effective dose and equivalent dose in 2 Gy fractions were widely recognised (>70%), while formal TCP and NTCP models were reported substantially less often (<35%). Radiobiological models were used for plan evaluation by 38.1% of respondents; dedicated software was uncommon (commercial 11.9%; open-source 2.4%). Routine clinical use of AI/ML was reported by 19.0% (95% CI 10.0%–33.3%), with auto-contouring the most frequently reported application (50.0%). Publication activity in this domain was low: 83.3% (95% CI 69.4%–91.7%) reported no peer-reviewed publications. The most frequently cited barriers were limited software access (45.2%), inadequate infrastructure (40.5%) and absence of clinical validation guidelines (31.0%).

Conclusion: In this small, self-selected sample, these exploratory findings describe a multilayered implementation gap spanning model calibration, plan evaluation, training and AI/ML adoption. They are hypothesis-generating rather than representative of national or global practice and indicate priorities for larger, geographically balanced studies and for the accompanying systematic review evidence synthesis (PROSPERO: CRD420251146188).

Keywords: *surveys and questionnaires*, *artificial intelligence*, *radiobiology*, *radiotherapy*, *treatment planning*, *low- and middle-income countries*, *TCP*, *NTCP*, *plan evaluation*

Research

Correspondence to: Kalyan Mondal
Email: kalyanmondal.res@gmail.com

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Introduction

Radiotherapy is central to cancer management, with approximately 50% of patients receiving radiation during their treatment course [1]. Low- and middle-income countries (LMICs) account for nearly 50% of global cancer deaths yet access only 5% of global radiotherapy resources [2,3]. Effective treatment planning requires maximising tumour control probability (TCP) while minimising normal tissue complication probability (NTCP) – a balance that radiobiological models have refined over five decades, from the foundational linear-quadratic (LQ) model through biologically effective dose (BED), equivalent dose in 2 Gy fractions (EQD2), generalised equivalent uniform dose (gEUD) and formal TCP/NTCP frameworks [4–9]. A clinically consequential yet underexplored application of these models is biological plan evaluation, wherein radiobiological indices complement conventional dose–volume metrics to inform plan selection and clinical decision-making [10]. For example, when two plans are dosimetrically comparable, NTCP estimates for parallel organs such as lung or parotid can identify the plan with the lower predicted complication risk; explicit TCP–NTCP trade-off analysis has also been used to individualise dose escalation and to select patients for proton therapy under model-based protocols [11,12].

Despite extensive model development, formal TCP/NTCP implementation in routine clinical practice remains limited across diverse healthcare systems; reviews from North America, Europe and Asia consistently report biologically based plan evaluation at a minority of centres, with physical dose–volume metrics remaining the clinical standard [13–16]. The Netherlands' national NTCP-based proton therapy selection protocol represents a notable exception, demonstrating feasibility when supported by national infrastructure and validated model sets [11,12]. Concurrently, artificial intelligence and machine learning (AI/ML) are transforming radiotherapy workflows across automated contouring, knowledge-based planning, dose prediction and outcome modelling [17–19], yet the 2024 AAPM–ESTRO guideline confirmed that clinical adoption remains limited relative to technological development [20]. Recent surveys indicate increasing AI use among European radiologists (48% in 2024), with significant disparities persisting between high-income countries (HICs) and LMICs [21,22].

In India, an estimated 1.46 million annual cancer cases coincide with persistent radiotherapy infrastructure deficits and workforce challenges [2,23,24]. While IMRT/VMAT adoption has improved substantially (~88% nationally [25]), integration of radiobiological optimisation and AI/ML-based plan evaluation into routine practice remains largely undocumented. Resource-constrained settings may derive disproportionate benefit from these tools: biological optimisation can help extract maximal therapeutic value from limited fractionation and machine capacity and standardise planning quality across heterogeneous centres, while AI-based automation can partially offset workforce shortages [22,26]. To our knowledge and based on a structured literature search of MEDLINE and PubMed (1975–2025) using combinations of the terms 'radiobiological model', 'TCP', 'NTCP', 'plan evaluation', 'artificial intelligence/machine learning' and 'survey', no prior study has jointly assessed classical radiobiological model adoption and AI/ML implementation with specific attention to plan evaluation practices and LMIC settings; existing surveys have addressed these domains separately [21,22,27].

This survey was designed as a pre-specified component of a mixed-methods systematic review registered with PROSPERO (CRD420251146188), enabling direct comparison between published evidence and clinical practice upon review completion. Specific objectives were as follows: (i) to characterise radiobiological model adoption and calibration practices; (ii) to assess AI/ML implementation patterns; (iii) to characterise radiobiological model use for plan evaluation; (iv) to identify barriers and training needs; and (v) to describe respondents' publication activity in this domain. The theme of this study is illustrated in Figure 1.

Methods

Study design and registration

This cross-sectional observational study was approved by the Institutional Review Board of GLA University, Mathura, India (September 23, 2025). It is a pre-specified component of a mixed-methods systematic review prospectively registered with PROSPERO on September 15, 2025 (CRD420251146188). The registered protocol names the survey component in its title and its secondary review question and prespecifies the target population (radiation oncology departments worldwide, with medical physicists, radiation oncologists and department heads as respondents), the survey domains and a descriptive analysis plan stratified by region and centre type. Because PROSPERO registers

systematic reviews and does not accept registrations of stand-alone cross-sectional surveys, the survey reported here is not itself separately registered, and no claim of independent registration is made. The registered protocol further specified a minimum of 20 responding centres per subcontinental region for quantitative regional synthesis, with regions below that threshold to be described narratively only; this pre-specified threshold governs how geography is reported here (Statistical Analysis). Informed electronic consent was obtained from all participants. The study was conducted in accordance with the Declaration of Helsinki and is reported according to the CHERRIES guidelines [28]. Upon systematic review completion, survey findings will be compared with the published literature synthesis.

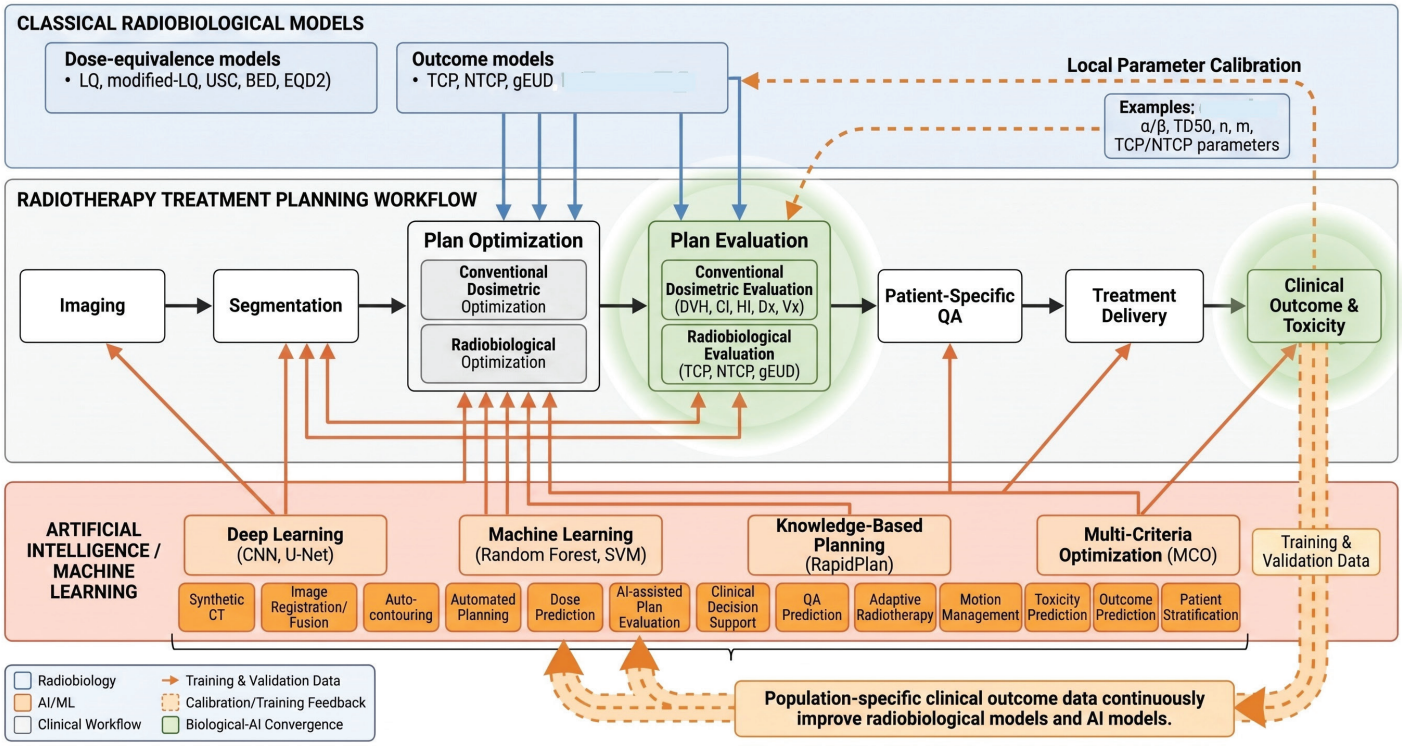


Figure 1. Conceptual overview of the study theme: the roles of classical radiobiological models and artificial intelligence/machine learning (AI/ML) across the radiotherapy treatment-planning workflow, with radiobiology-based plan evaluation as the focus. Top (blue): classical radiobiological models – dose-equivalence models (linear-quadratic, LQ; modified-LQ; universal survival curve, USC; biologically effective dose, BED; equivalent dose in 2 Gy fractions, EQD2) and outcome models (tumour control probability, TCP; normal tissue complication probability, NTCP; generalised equivalent uniform dose, gEUD). Middle (grey): the clinical workflow – imaging, segmentation, plan optimisation, plan evaluation, patient-specific quality assurance (QA), treatment delivery and clinical outcome and toxicity; plan optimisation and plan evaluation each combine a conventional dosimetric component (dose–volume histogram, DVH; conformity index, CI; homogeneity index, HI; Dx; Vx) and a radiobiological component (TCP/NTCP/gEUD). Bottom (orange): AI/ML methods – deep learning (convolutional neural network, CNN; U-Net), machine learning (random forest, RF; support vector machine, SVM), knowledge-based planning (RapidPlan) and multi-criteria optimisation (MCO)– and their applications across the workflow (synthetic CT, image registration/fusion, auto-contouring, automated planning, dose prediction, AI-assisted plan evaluation, clinical decision support, QA prediction, adaptive radiotherapy, motion management, toxicity prediction, outcome prediction and patient stratification). Radiobiological models inform plan optimisation and, in particular, plan evaluation (green, biological–AI convergence), where radiobiological indices complement conventional dosimetric evaluation, while AI/ML methods act as data-driven counterparts across the same stages. Population-specific clinical-outcome data are fed back (dashed) to locally calibrate radiobiological model parameters (e.g. α/β, TD50, n, m) and to continuously train and validate AI models, supporting biologically informed, AI-augmented personalised radiotherapy. Created with BioRender.com.

Survey instrument

The 40-item questionnaire comprised six domains: (1) demographics and institutional characteristics; (2) clinical infrastructure; (3) radiobiological model usage, calibration and documentation; (4) AI/ML implementation; (5) plan evaluation tools and barriers and (6) training needs and research activity. Question types included single-select, multiple-select, Likert scales and ranking items. The instrument was developed iteratively by the investigator team with expertise in medical physics, radiation oncology, radiobiology and AI/ML and pilot-tested with five colleagues (three medical physicists and two radiation oncologists) across Indian radiation oncology departments prior to full distribution. The full instrument is provided in Supplementary Table S1. To reduce interpretive variability, key response options were anchored with explicit descriptors: AI/ML status used the categories 'routine clinical use (fully integrated)', 'limited clinical implementation (pilot)', 'planning to implement' and 'not using', and frequency of radiobiological model use was banded by percentage of cases (>75%, 50%–75%, 25%–50%, <25%, never). A four-step data quality assurance (QA) protocol assessed completeness, internal consistency, plausibility and discordance. Item-level completeness was 100% for demographics and clinical infrastructure and ranged from 88.1% to 97.6% across the radiobiological-model, plan-evaluation, training and publication items; it was 81.0% for implementation methods, 76.2% for the barriers item and 64.3%–66.7% for the items answered only by respondents currently using AI/ML. The number of respondents who did not answer each item is stated in the corresponding table. Full QA results are provided in Supplementary Table S2.

Survey distribution

A multi-channel distribution strategy was employed: the global MEDPHYS mailing list (>4,000 subscribers) with an initial invitation (November 4, 2025) and reminder (January 13, 2026); direct email to >300 Indian radiation oncology professionals; dissemination via AMPI, EFOMP and AFOMP; and LinkedIn, Facebook and WhatsApp professional groups. The survey was open October 28, 2025–February 20, 2026 (117 days); all 42 responses were received within the first 83 days of the active window.

Participation was open to practising radiation oncology professionals (medical physicists, radiation oncologists, dosimetrists and radiotherapy researchers) involved in treatment planning or evaluation; a pre-survey consent item screened participants, and non-consenting respondents exited automatically. Duplicate submissions were limited by the platform's one-response-per-account setting and screened during quality assurance by cross-checking demographic, institutional and infrastructure responses; no duplicate patterns were detected. Because the instrument was disseminated through overlapping open channels with unavoidable audience overlap, the number of eligible individuals who viewed the invitation cannot be established; consequently, CHERRIES view, participation and completion rates and a true response rate cannot be calculated. Instrument validation comprised iterative content review by the multidisciplinary investigator team and pilot testing with five colleagues; formal psychometric validation was not undertaken, consistent with the study's exploratory objective.

Statistical analysis

The analysis is descriptive throughout. Categorical variables are reported as frequencies and percentages with Wilson score 95% confidence intervals. No inferential testing between geographical subgroups was performed. The registered protocol required a minimum of 20 responding centres per subcontinental region before a region could enter quantitative synthesis, and specified that regions falling below that threshold would be described narratively only; no region other than South Asia reached this threshold in the present sample (respondents practising outside India, n = 12 across nine countries). Country of practice is therefore reported descriptively and no India-versus-international comparison is presented. All proportions are calculated on the full sample (N = 42); every table reports the number of respondents who did not answer that item, so single-select items sum to 42, while multiple-select items may sum to more than 100%. Exploratory stratification by profession and institution type is reported descriptively, without significance testing, in Supplementary Table S3. Analyses were performed in Python 3.12 with pandas and NumPy, and all tables and figures were regenerated directly from the de-identified response file deposited at Zenodo.

Results

Participant demographics and geographic distribution

Forty-two valid responses were received from 10 countries across five continental regions (Fig. 2). India contributed 71.4% (*n* = 30), followed by the United States (*n* = 3, 7.1%), Germany (*n* = 2, 4.8%), and one respondent each from seven other countries; no region other than South Asia reached the 20-centre threshold pre-specified in the registered protocol for regional quantitative synthesis. Medical physicists comprised 78.6% (*n* = 33), radiation oncologists 19.0% (*n* = 8) and research scientists 2.4% (*n* = 1). Experience was distributed across career stages, with 2–5 years the most common group (26.2%, 11/42; two respondents did not state their experience). Full demographic and institutional characteristics are presented in Table 1; geographic and professional details are provided in Supplementary Figure S3.

Clinical infrastructure

Advanced EBRT capabilities were widely available: VMAT (88.1%), IMRT (85.7%), IGRT-CBCT (81.0%), 3DCRT (78.6%), SBRT (59.5%) and SRT (54.8%; Fig. 3A). Eclipse™ was the most frequently reported treatment planning system (26 of 52 selections, 50.0%), followed by Monaco™ (23.1%), Telecobalt-based systems (7.7%) and Precision™ (5.8%); one respondent did not answer this item (Fig. 3B). Brachytherapy was available at 83.3% of centres. These findings are broadly consistent with published analyses of India's installed radiotherapy fleet [25,29].

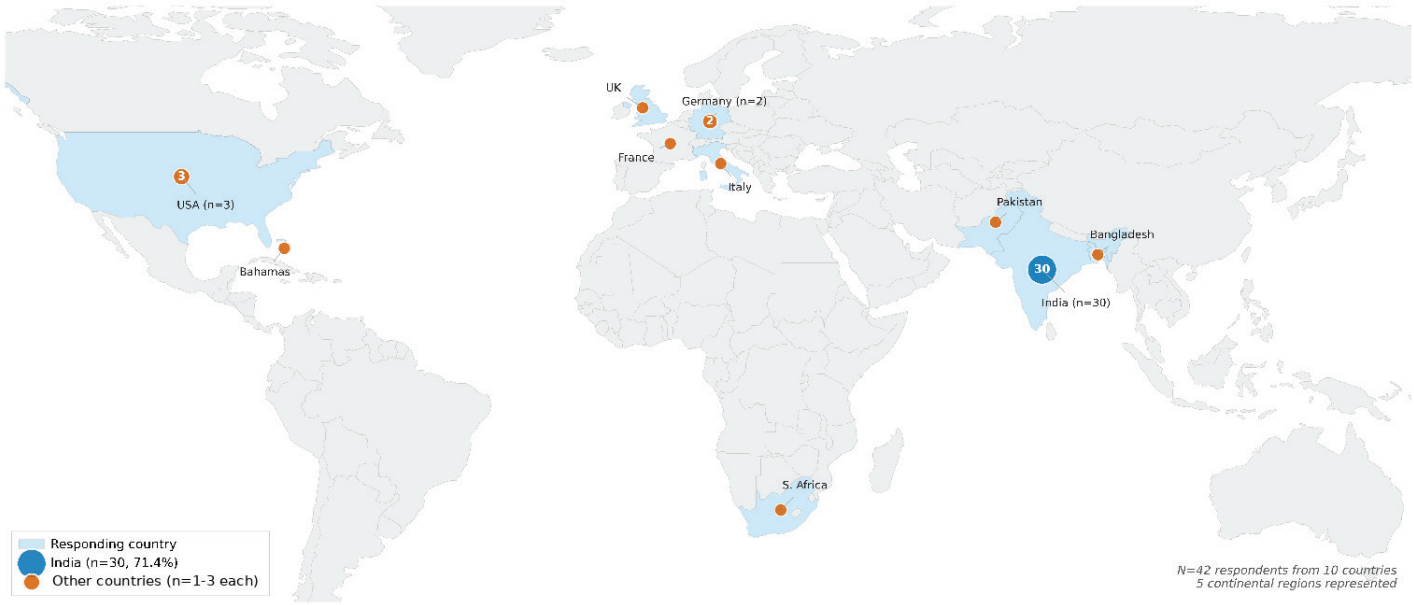


Figure 2. Global distribution of survey respondents (*N* = 42; 10 countries, 5 continental regions). Bubble size is proportional to the square root of respondent count. India (*n* = 30, 71.4%) is shown in blue; all other contributing countries in orange. Shaded country borders indicate responding nations.

Research

Table 1. Demographic and institutional characteristics of survey respondents (*N* = 42).

Characteristic	Category	*n*	%
Country	India	30	71.4
	United States	3	7.1
	Germany	2	4.8
	Others (7 countries)	7	16.7
Professional role	Medical physicist	33	78.6
	Radiation oncologist	8	19.0
	Research scientist	1	2.4
Experience	<2 years	5	11.9
	2–5 years	11	26.2
	6–10 years	9	21.4
	11–20 years	7	16.7
	>20 years	8	19.0
	Not stated	2	4.8
Institution type	Private hospital	14	33.3
	Academic hospital	11	26.2
	Medical college/University	8	19.0
	Government hospital	4	9.5
	Cancer research centre + community hospital	4	9.5
	Not stated	1	2.4
Annual patient load	<500	15	35.7
	500–1,999	9	21.4
	2,000–9,999	11	26.2
	≥10,000	4	9.5
	Information not available	1	2.4
	Not stated	2	4.8

Countries in the 'Others' category: United Kingdom, Pakistan, Italy, Bahamas, South Africa, France and Bangladesh (*n* = 1 each). All percentages are calculated on the full sample (*N* = 42); respondents who did not answer an item are shown as a separate category so that every item sums to 42. Institution type groups private hospital with private clinic; academic hospital includes one government-owned academic teaching institute; government hospital includes public (government-owned) hospitals; and the final category combines cancer research centre (*n* = 3) with community hospital (*n* = 1)

Radiobiological model adoption and calibration practices

Local parameter calibration to the institution's own patient population was confirmed by 14.3% (6/42; 95% CI 6.7%–27.8%) of respondents. An equal number reported no calibration (40.5%, 17/42; 95% CI 27.0%–55.5%) and did not know their institution's calibration status (40.5%, 17/42; 95% CI 27.0%–55.5%); two respondents did not answer the item (Table 2; Supplementary Fig. S2A). These categories are reported separately throughout: uncertainty about calibration status is not evidence that calibration is absent, and the proportion of respondents unable to state whether their own institution calibrates its model parameters is itself a finding. Parameter sources were predominantly published literature values (52.4%), which are largely Western-derived.

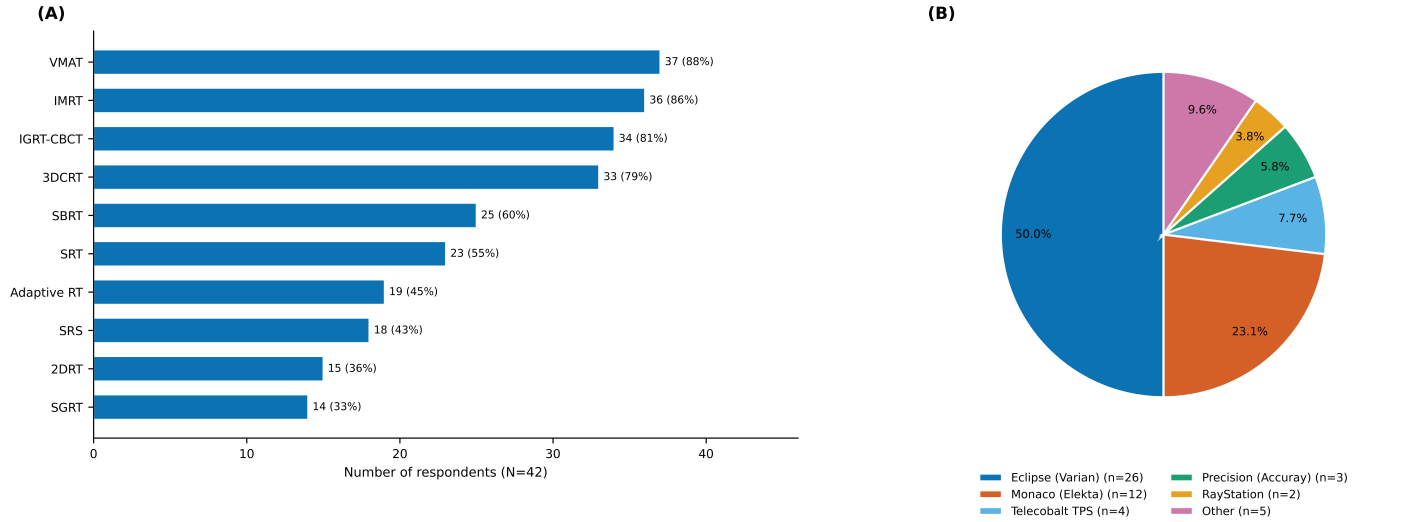


Figure 3. Clinical infrastructure at responding institutions. (A) Availability of external beam radiotherapy (EBRT) modalities (multiple selections permitted); bars show the number of respondents reporting each modality (*N* = 42). (B) Distribution of treatment planning systems (TPS) in use (multiple selections permitted; *n* = 52 TPS selections from the 41 respondents who answered this item, shown as pie slices). CBCT = cone-beam computed tomography; IGRT = image-guided radiotherapy; IMRT = intensity-modulated radiotherapy; SBRT = stereotactic body radiotherapy; SRT = stereotactic radiotherapy; VMAT = volumetric modulated arc therapy.

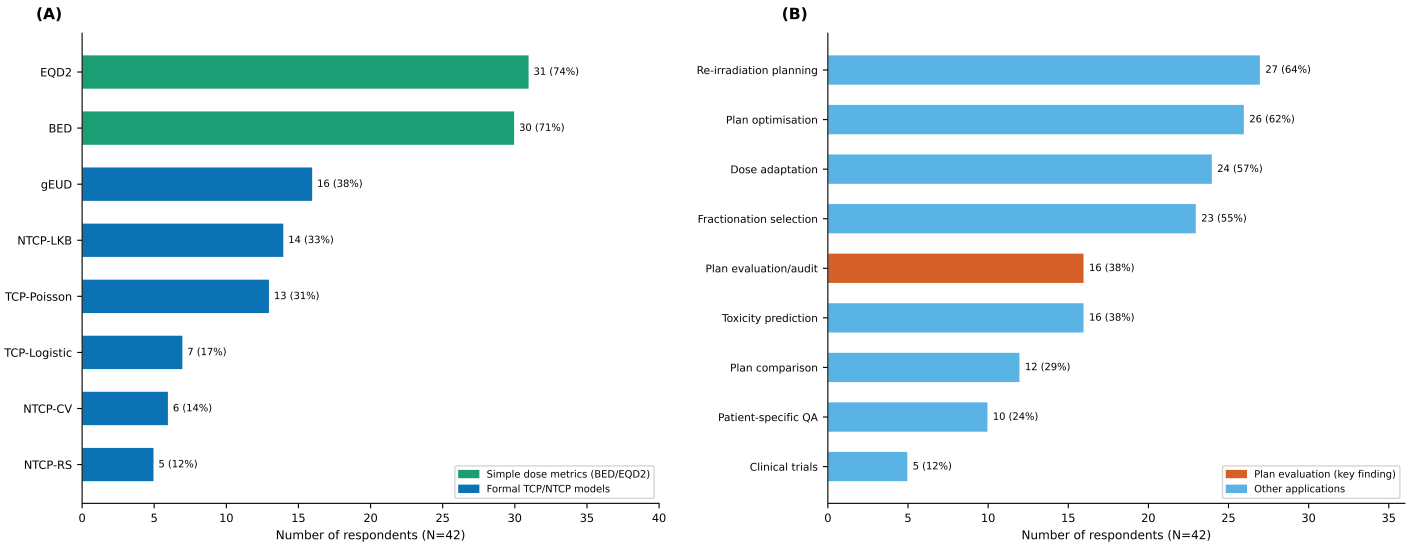


Figure 4. Radiobiological model adoption (*N* = 42; multiple selections permitted in both panels; percentages calculated on the full sample). (A) Specific radiobiological models or dose metrics recognised and used (answered by 37 respondents): green bars denote simple dose metrics (BED, biologically effective dose; EQD2, equivalent dose in 2 Gy fractions); blue bars denote formal models (gEUD, generalised equivalent uniform dose; TCP, tumour control probability; NTCP, normal tissue complication probability; LKB, Lyman–Kutcher–Burman). (B) Clinical contexts in which radiobiological models are applied (answered by 39 respondents); the red bar highlights plan evaluation/audit (key finding, 38.1%) and blue bars denote other applications.

Table 2. Radiobiological model adoption, calibration practices and plan evaluation type (*N* = 42).

Domain	Category	*n*	%	95% CI
Frequency of use (*N* = 42)	Daily/routine (>75%)	4	9.5	3.8–22.1
	Frequent (50%–75%)	5	11.9	5.2–25.0
	Occasional (25%–50%)	9	21.4	11.7–35.9
	Rare (<25%)	14	33.3	21.0–48.4
	Never	7	16.7	8.3–30.6
	Other (free-text response)	1	2.4	0.4–12.3
	Not stated	2	4.8	1.3–15.8
Local parameter calibration (*N* = 42)	Yes	6	14.3	6.7–27.8
	No	17	40.5	27.0–55.5
	Calibration status not known ('Not sure')	17	40.5	27.0–55.5
	Not stated	2	4.8	1.3–15.8
Parameter source (multiple)	Published literature	22	52.4	37.7–66.6
	National/international guidelines	4	9.5	3.8–22.1
	TPS default values	4	9.5	3.8–22.1
	Clinical trial protocols	4	9.5	3.8–22.1
	Local institutional data	2	4.8	1.3–15.8
	Not sure of parameter source	2	4.8	1.3–15.8
	Not stated	4	9.5	3.8–22.1
Plan evaluation type (multiple)	Physical DVH-based	31	73.8	58.9–84.7
	Radiobiological	16	38.1	25.0–53.2
	AI/ML-capable	4	9.5	3.8–22.1
	Not stated	6	14.3	6.7–27.8

All percentages are calculated on the full sample (*N* = 42) and 95% confidence intervals are Wilson score intervals. For the two single-select domains ('Frequency of use' and 'Local parameter calibration'), every respondent is accounted for, including free-text and unanswered responses, so those categories sum to 42. 'Parameter source' and 'Plan evaluation type' permit multiple selections, so their totals may exceed 100%; the number of respondents who did not answer each item is given. 'Calibration status not known' corresponds to the 'Not sure' response option and is reported separately from 'No', because uncertainty about institutional practice is not evidence that calibration is absent

Formal clinical use of radiobiological models was generally infrequent: 9.5% used them in routine practice (>75% of cases), 33.3% rarely (<25%) and 16.7% never; one respondent described a non-standard pattern of use in free text, and two did not answer the item. BED and EQD2 were the most widely recognised models (71.4% and 73.8%, respectively), consistent with their integration into fractionation guidelines [5,30,31]. Formal TCP/NTCP models were reported substantially less often: gEUD (38.1%), NTCP-LKB (33.3%), TCP-Poisson (31.0%), TCP-Logistic (16.7%), NTCP-Critical Volume (14.3%) and NTCP-Relative Seriality (11.9%; Fig. 4A); five respondents did not answer this item.

The most common contexts for radiobiological model use were re-irradiation planning (64.3%), plan optimisation (61.9%) and dose prescription adaptation (57.1%; Fig. 4B); three respondents did not answer this item. Notably, 38.1% (16/42) used radiobiological models for plan evaluation or audit – fewer than for re-irradiation planning, plan optimisation or dose adaptation. Documentation practices were variable: 19.0% routinely included radiobiological calculations in treatment planning records (Supplementary Fig. S2B). In exploratory stratification (descriptive only, given small strata), confirmed local calibration occurred exclusively at academic/teaching institutions (6/22) and at no non-academic centre (0/19), while all respondents reporting routine AI/ML clinical use were medical physicists (8/33; 0/8 radiation oncologists); these unadjusted patterns are hypothesis-generating (Supplementary Table S3).

AI/ML implementation

The AI/ML landscape reflected a field in early transition: 19.0% (8/42; 95% CI 10.0%–33.3%) reported routine clinical use, 33.3% had no plans to implement, 16.7% were planning implementation within 1 year and 9.5% were in limited pilot testing; a further 14.3% described other statuses in free text (research use only, testing or validation or implementation planned beyond 1 year), and 7.1% did not answer the item (Fig. 5A).

Auto-contouring/segmentation was the most widely reported AI application (50.0%), followed by plan optimisation (28.6%) and automated planning (26.2%; Fig. 5B); this item was answered by the 28 respondents reporting any AI/ML activity, and percentages are calculated on the full sample. AI-based plan evaluation (16.7%) and toxicity/outcome prediction (11.9%) – representing the convergence of radiobiological models and AI/ML – were among the least frequently reported applications, despite favourable predictive performance in several published cohorts [32–34]. AI/ML validation and monitoring practices were limited relative to recommended standards [20]: 11.9% reported prospective clinical validation and 23.8% reported no formal monitoring programme (Supplementary Fig. S1); these items were answered by 27 and 28 respondents, respectively.

Barriers, training needs and plan evaluation tools

The most frequently reported barriers overall were limited software access (45.2%), inadequate infrastructure (40.5%) and lack of clinical validation or guidelines (31.0%; Table 3; Fig. 6A). This item was answered by 32 of 42 respondents (76.2%), the lowest completeness of any item; percentages are calculated on the full sample, so the frequency of each barrier among respondents who did answer is correspondingly higher than the values shown.

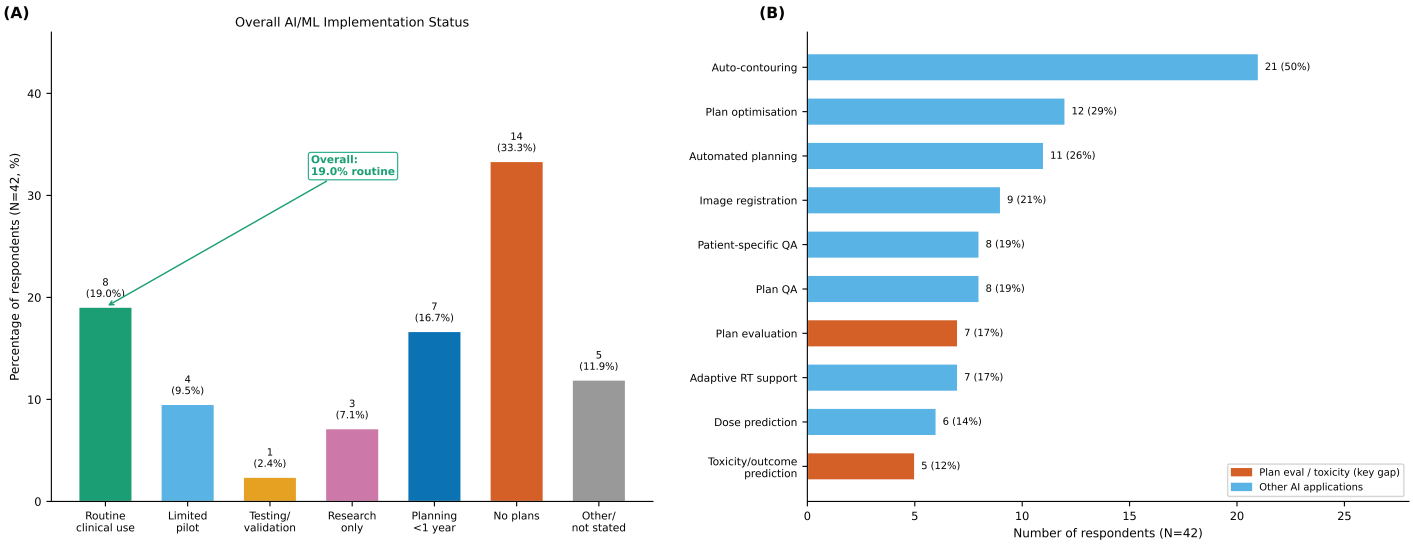


Figure 5. Artificial intelligence/machine learning (AI/ML) implementation (*N* = 42; percentages calculated on the full sample). (A) Overall distribution of AI/ML implementation status across all respondents; each colour represents one implementation stage, the final bar combines free-text statuses with unanswered responses and the overall routine clinical use rate (19.0%) is annotated. (B) AI/ML applications currently used or under evaluation (multiple selections permitted; answered by 28 respondents); red bars highlight AI-aided plan evaluation and toxicity/outcome prediction, the lowest-adoption applications despite high potential convergence with radiobiological modelling.

Table 3. Barriers to adoption of radiobiological models and AI/ML (*N* = 42).

Barrier	*n* (overall)	% (*N* = 42)
Limited software access	19	45.2
Inadequate infrastructure / TPS capabilities	17	40.5
Lack of clinical validation or guidelines	13	31.0
Limited awareness of AI/ML approaches	12	28.6
Insufficient expertise or training	11	26.2
Limited funding or financial resources	11	26.2
Lack of institutional support	8	19.0
Poor data quality or missing datasets	7	16.7
Regulatory or ethical approval delays	4	9.5
Other (weak IT support)	1	2.4
Not stated	10	23.8

Multiple selections permitted; totals may exceed 100%. Percentages are calculated on the full sample (*N* = 42); ten respondents (23.8%) did not answer this item and are shown as a separate row

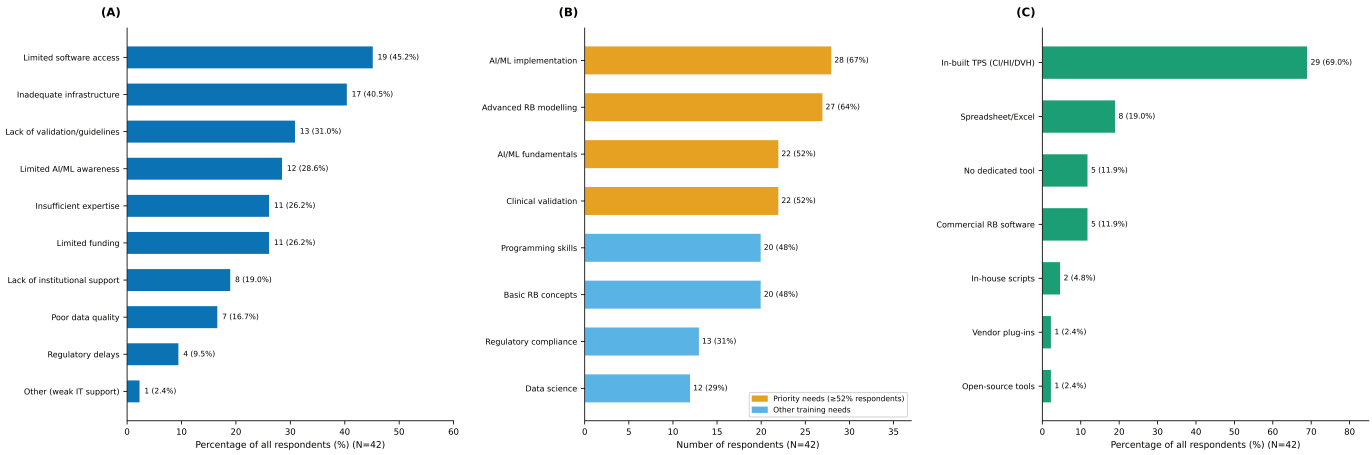


Figure 6. Barriers, training needs and plan evaluation tools (*N* = 42; multiple selections permitted in all panels; percentages calculated on the full sample). (A) Barriers to adopting radiobiological models and AI/ML (answered by 32 respondents). (B) Training needs ranked by respondents (answered by 38 respondents); orange bars indicate priority needs (≥52% endorsement). (C) Plan evaluation tools used (answered by 40 respondents). CI = conformity index; HI = homogeneity index; DVH = dose–volume histogram; RB = radiobiological.

A training deficit was reported: 38.1% of respondents (16/42; 95% CI 25.0%–53.2%) had received no formal training in radiobiological modelling or AI/ML; five respondents did not answer this item. Top-ranked training needs were AI/ML implementation (66.7%), advanced radiobiological modelling (64.3%) and, jointly, AI/ML fundamentals and clinical validation methods (52.4% each; Fig. 6B); four respondents did not answer this item.

Plan evaluation tool use was dominated by built-in TPS modules (69.0%), followed by spreadsheet-based calculations (19.0%; Table 4; Fig. 6C); two respondents did not answer this item. Dedicated radiobiological software was reported by 11.9% (commercial: BioSuite [35], dose–volume histogram (DVH) Analyser [36] and PlanIQ [37]) and 2.4% (open-source: CERR [38], DREES [39], HART [40], RADBIOMOD [41] and RBMODELv1 [42]); 85.7% reported using neither. Publication activity in this domain was low: 83.3% (35/42; 95% CI 69.4%–91.7%) reported

no peer-reviewed publications on radiobiological modelling or AI/ML in radiotherapy, and three respondents did not answer the item. This measures the research output of the respondents rather than the quality of their clinical practice; no directly comparable published estimate was identified.

The key observations of this study are given in Table 5.

Table 4. Plan evaluation tools used (*N* = 42).

Tool category	*n*	% (*N* = 42)	95% CI
In-built TPS modules (conformity index, homogeneity index, DVH-based)	29	69.0	54.0–80.9
Spreadsheet/Excel-based calculations	8	19.0	10.0–33.3
No dedicated tool – manual/visual only	5	11.9	5.2–25.0
Commercial RB software (BioSuite, DVH Analyser and PlanIQ)	5	11.9	5.2–25.0
In-house MATLAB/Python/R scripts	2	4.8	1.3–15.8
Vendor plug-ins or macros within TPS	1	2.4	0.4–12.3
Open-source research tools (CERR, DREES, HART, RADBIOMOD, RBMODELv1)	1	2.4	0.4–12.3
Not stated	2	4.8	1.3–15.8

Multiple selections permitted; totals may exceed 100%. Percentages are calculated on the full sample (*N* = 42) and 95% confidence intervals are Wilson score intervals; two respondents did not answer this item. DVH = dose–volume histogram; RB = radiobiological

Table 5. Key findings and suggested priorities for future research.

Key finding (95% CI)	Suggested priority for future research
Confirmed local calibration 14.3% (6.7%–27.8%); no calibration 40.5% (27.0%–55.5%); calibration status not known 40.5% (27.0%–55.5%)	Multicentre outcome-data pooling and local parameter calibration, along with investigation of why calibration status is frequently unknown to practitioners, are priorities for investigation before biological plan evaluation can inform decisions.
Radiobiological models for plan evaluation 38.1% (25.0%–53.2%); dedicated software <15%	Evaluate whether integrating validated, accessible (ideally open-source) radiobiological evaluation tools within commercial TPS changes evaluation practice.
Overall AI/ML routine use 19.0% (10.0%–33.3%); auto-contouring dominant (50%)	Examine staged AI/ML adoption with validation and monitoring aligned to AAPM–ESTRO guidance [20].
No formal training 38.1% (25.0%–53.2%)	Assess whether structured radiobiology/AI training embedded within professional-society and institutional programmes addresses the reported deficit.
No publications in this domain: 83.3% (69.4%–91.7%)	Investigate whether local research and audit capacity can generate the outcome data required for calibration.

All proportions are calculated on *N* = 42; 95% CIs are Wilson score intervals. The right-hand column lists priorities for future research that follow from these exploratory findings; they are not evidence-based recommendations for clinical practice and have not been evaluated as interventions

Discussion

The radiobiological model paradox and calibration practice

The finding that BED/EQD2 are widely recognised (>70%) while formal TCP/NTCP models remain less used (<35%) reflects a persistent paradox: despite five decades of model development, the tools most capable of informing individualised treatment decisions have the lowest clinical penetration [14,15]. This is consistent with Yorke's characterisation of achieving high TCP with low NTCP as still 'challenging' due to insufficient integration of dosimetric and clinical correlates into decision workflows [13], and with broader assessments of formal TCP/NTCP use as 'still limited' in most clinical settings [14,15]. The Netherlands' NTCP-based proton therapy selection protocol [11,12] demonstrates feasibility when national infrastructure, validated model sets and institutional research capacity are in place – prerequisites that most centres in this small sample did not report. These findings (Table 5) are summarised in the conceptual framework (Fig. 7), which is descriptive and hypothesis-generating rather than a validated model; it annotates each pipeline stage with the corresponding survey-derived observation.

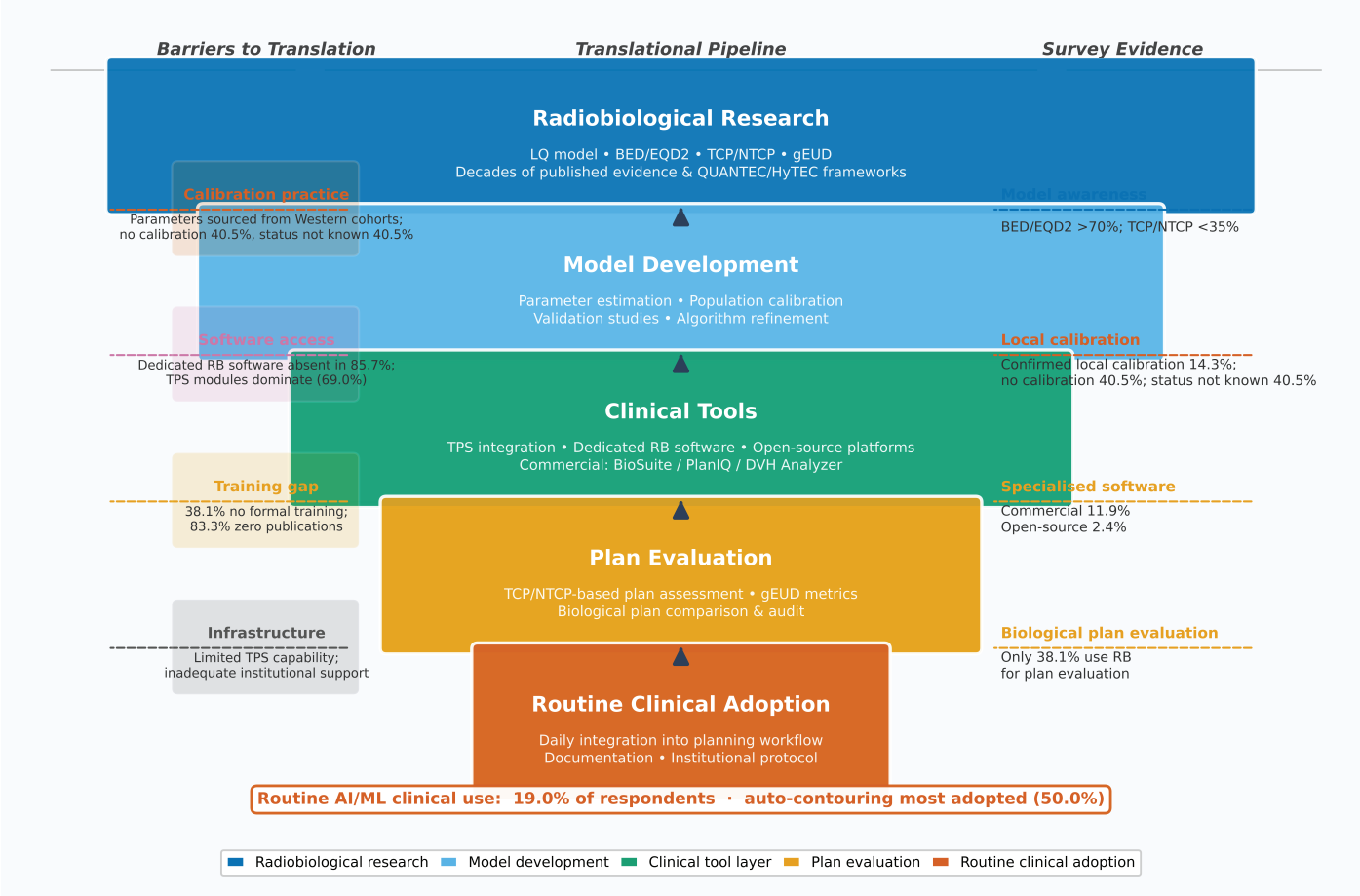


Figure 7. Conceptual framework depicting the translational pipeline from radiobiological research to routine clinical adoption. Five pipeline stages (coloured funnel boxes) are annotated by barriers (left) and survey-derived descriptive evidence (right). The bottom bar summarises overall routine AI/ML use across all respondents. Stage annotations are illustrative and derived from this exploratory survey of 42 self-selected respondents; the framework is not a validated model.

Calibration practice warrants separate consideration. Confirmed local calibration was uncommon (14.3%), and an equal number of respondents reported no calibration (40.5%) as were unable to state their institution's calibration status (40.5%). These two groups are distinct and are not combined here. Where calibration is confirmed absent, radiobiological plan evaluation may carry uncertainty of unquantified magnitude, the clinical impact of which cannot be determined from these data and warrants formal investigation. Where calibration status is simply unknown to the respondent, the finding speaks to awareness and documentation rather than to the underlying practice: an institution may calibrate without that being visible to the individual preparing or checking the plan. That four in ten respondents could not answer this question about their own department is, on its own terms, a notable observation and a candidate subject for future study. The QUANTEC initiative established dose–volume–outcome relationships predominantly from Western cohorts [30], and subsequent validation studies have demonstrated that model performance varies significantly across populations and treatment techniques [4]. For diverse patient populations – where genetic polymorphisms, comorbidity patterns, nutritional status and treatment delivery variations may differ from derivation cohorts [43] – application of uncalibrated parameters creates systematic uncertainty in predicted TCP/NTCP values [44,45]. Low reported publication activity (83.3% with no publications) may be relevant here because locally generated outcome data are what the iterative calibration cycle requires. Publication output is, however, a measure of research activity rather than of clinical practice or competence and should be read only as an indicator of limited local outcome-data generation.

The plan evaluation gap

In this sample, 38.1% of respondents used radiobiological models for plan evaluation, and dedicated evaluation software was reported by 14.3% – consistent with a specific translational gap, although the sample is too small and too geographically skewed to establish its extent. Physical DVH metrics remained dominant (73.8%), and the scarcity of purpose-built radiobiological evaluation tools in these clinical environments is consistent with the divide described between published evaluation methodology and clinical implementation [16,46]. Recent validation studies further underscore that NTCP model performance varies substantially across cohorts [47], reinforcing the case for population-specific calibration as a prerequisite for valid biological plan evaluation. Two questions follow for future research: whether integrating validated radiobiological evaluation tools within commercial TPS platforms changes evaluation practice, and whether institutional pipelines for population-specific outcome data collection can support parameter calibration – the latter being an objective of the accompanying systematic review. Candidate topics for that work include multicentre collaborations to pool population-specific outcome data, prospective validation studies preceding clinical use, structured training embedded in professional-society programmes and accessible, ideally open-source, radiobiological evaluation tools within commercial TPS platforms. These are research priorities suggested by an exploratory sample, not recommendations for practice.

AI/ML adoption and the unexplored convergence

The overall 19.0% routine use rate, with auto-contouring as the most frequently reported application (50.0%), is consistent with the documented AI maturity hierarchy in radiotherapy [18–20], corroborated by a systematic overview of AI-based applications that identified auto-contouring as the most widely implemented modality with substantial geographic disparities [48], and with broader surveys reporting LMIC–HIC adoption disparities [21,22]. The present sample contains too few respondents outside South Asia to support regional comparison, so this survey cannot test whether such disparities are present in its own data, and no comparison between Indian and other respondents is reported. The barriers most frequently endorsed overall – limited software access, inadequate infrastructure and absence of clinical validation guidance – span both infrastructure and evidence-translation categories, and are consistent with those described by Petragallo *et al* [27] and by a systematic review of AI implementation barriers across healthcare settings [49].

The convergence of radiobiological modelling with AI/ML for personalised plan evaluation – where machine learning approaches have demonstrated favourable predictive performance relative to classical NTCP models [32,34,50] – was rarely reported in this sample: AI-based toxicity prediction (11.9%) and AI-aided plan evaluation (16.7%) were among the least frequently reported applications. Whether this reflects a general pattern cannot be determined from 42 self-selected respondents, but it identifies a question worth addressing in future implementation research. Adoption is also shaped by factors this instrument did not measure – integration into existing clinical workflows, the

complexity and opacity of some models, absence of reimbursement pathways and medico-legal and regulatory uncertainty around model-guided decisions.

Contributions and limitations

This study contributes several observations. Based on the structured search underpinning our registered systematic review, we are not aware of a previous survey that reports, within a single instrument, publication activity in this domain (83.3% with no publications), local calibration practice (14.3% confirmed calibration; 40.5% no calibration; 40.5% status not known) and radiobiological model use specifically for plan evaluation (38.1%). A substantial training deficit was also reported (38.1% with no formal training). As a pre-specified component of a registered systematic review, the data provide an empirical complement to the published evidence base for integration upon review completion. These observations describe the respondents to this survey and are offered as a starting point for larger studies rather than as an estimate of practice in any country, region or income group.

Several limitations must be acknowledged, and they bound the interpretation of every finding above. The sample size (N = 42) is small, though comparable to published surveys in specialised radiotherapy communities [22,27], and supports exploratory description only. The sample is a self-selected convenience sample recruited through open channels; it is not statistically representative of national or global practice, and no finding here should be read as an estimate of practice in any country, region or income group. The geographic distribution is heavily weighted towards India (71.4%); the 12 respondents practising in nine other countries are too few, and too heterogeneous in health system and resource level, to constitute a comparator group, and the 20-centre-per-region threshold pre-specified in the registered protocol was not met outside South Asia. Country of practice is therefore reported descriptively only, and no India-versus-international comparison is presented. Although institution type and patient load were captured, staffing levels and a full technology inventory were not; these unmeasured institutional factors may influence adoption and warrant more granular future surveys. Approximate engagement from the MEDPHYS listserv (~1%) is consistent with norms for unsolicited online professional surveys [51,52]; because the instrument was disseminated through overlapping open channels, the true eligible denominator – and therefore a genuine response rate – cannot be calculated, so the magnitude of non-response and self-selection bias cannot be quantified. Self-reported data carry inherent social desirability bias, which may inflate reported adoption. Item non-response varied by domain, from none for demographics and infrastructure to 23.8% for the barriers item; because percentages are calculated on the full sample throughout, reported proportions are conservative for items with missing responses. The calibration question did not allow respondents to distinguish between active institutional calibration unknown to the individual and confirmed absence of any calibration process, which is why 'not sure' responses are reported as a separate category throughout rather than combined with 'no'. Internal consistency analysis identified 9.5% response discordance, indicating some measurement imprecision. Within these limits, concordance of key infrastructure findings with published benchmarks (Supplementary Table S4), high completeness for the core items, and transparent QA reporting support the internal validity of the descriptive findings.

Conclusion

Among 42 self-selected respondents, this exploratory survey describes a multi-layered implementation gap in radiotherapy treatment planning – spanning model calibration, biological plan evaluation, training and AI/ML adoption. The sample is small and predominantly Indian, so these observations are hypothesis-generating and are not offered as a description of national or global practice. They indicate priorities for future research: confirming the calibration and plan-evaluation findings in larger, geographically balanced samples; establishing why calibration status is so frequently unknown to practitioners and evaluating whether accessible evaluation software and structured training alter practice. The datas*et al*so provides the practice-side input for integration with the accompanying systematic review evidence synthesis (PROSPERO: CRD420251146188).

List of abbreviations

AAPM, American Association of Physicists in Medicine; AI/ML, Artificial intelligence/machine learning; API, Application Programming Interface; BED, Biologically effective dose; CBCT, Cone-beam computed tomography; CI, Conformity index (statistics: confidence interval, stated

where used); CI, Confidence interval (statistical); CNN, Convolutional neural network; DVH, Dose–volume histogram; EBRT, External beam radiotherapy; EQD2, Equivalent dose in 2 Gy fractions; ESAPI, Eclipse Scripting Application Programming Interface; ESTRO, European Society for Radiotherapy and Oncology; gEUD, Generalised equivalent uniform dose; HDR, High dose rate; HI, Homogeneity index; IGRT, Image-guided radiotherapy; IMRT, Intensity-modulated radiotherapy; KBP, Knowledge-based planning; LDR, Low dose rate; LKB, Lyman–Kutcher–Burman; LMIC, Low- and middle-income country; LQ, Linear-quadratic; NTCP, Normal tissue complication probability; PDR, Pulsed dose rate; QA, Quality assurance; RB, Radiobiological; SBRT, Stereotactic body radiotherapy; SRS, Stereotactic radiosurgery; SRT, Stereotactic radiotherapy; SVM, Support vector machine; U-Net, a convolutional network architecture for biomedical image segmentation; VMAT, Volumetric modulated arc therapy; 2DRT, Two-dimensional conventional radiotherapy.

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Conflicts of interest

One of the authors (Abhijit Mandal) is a co-developer of the software RBMODELv1 [42]. The other authors declare no competing interests.

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Author contributions

KM: Conceptualisation, methodology, survey design, data collection, formal analysis and manuscript writing. AM: Conceptualisation, survey design, supervision, analysis review and manuscript editing. AV: Survey design, Supervision, resources, approval and manuscript review.

Ethics approval and consent to participate

This study was approved by the Institutional Review Board (IRB) of GLA University, Mathura, India (approval date: 23 September 2025). Informed consent was obtained electronically from all participants prior to survey participation. The study was conducted in accordance with the Declaration of Helsinki.

PROSPERO Registration

The parent mixed-methods systematic review is prospectively registered with PROSPERO (CRD420251146188; registered 15 September 2025): https://www.crd.york.ac.uk/PROSPERO/view/CRD420251146188. The cross-sectional survey reported here is a pre-specified component of that registered protocol. PROSPERO registers systematic reviews and does not accept registrations of stand-alone surveys, so the survey is not separately registered.

Data availability

The full survey instrument is provided in Supplementary Table S1. De-identified survey response data are deposited at Zenodo (https://doi.org/10.5281/zenodo.19062182).

AI Disclosure

AI-assisted tools (Claude Sonnet 4.6, Anthropic PBC, 2026) were used for language editing and manuscript formatting. All scientific content, data analysis, interpretation and conclusions are the responsibility of the authors.

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Supplementary materials

The following 40-item questionnaire was hosted on Google Forms (Google LLC, Mountain View, CA, USA), 28 October 2025 – 20 February 2026. Items are organised by domain. Estimated completion time: 10 minutes (approximately). De-identified aggregate responses are publicly available at the link provided in the main text.

Supplementary Table S1. Full survey instrument.

Item No.	Domain	Question text	Type	Response options
—	*Pre-survey*	Do you agree to participate in this anonymous survey?	Single-select	Yes / No (exit if No)
1	Demographics	Country of practice	Free text / dropdown	[Country name]
2	Demographics	Institution type *(optional)*	Single-select	Private hospital / Academic hospital / Government hospital / Medical college or university / Cancer research centre / Community hospital / Other
3	Demographics	Annual radiotherapy patient load *(optional)*	Single-select	<500 / 500–1,999 / 2,000–9,999 / ≥10,000 / Information not available
4	Demographics	Primary professional role	Single-select	Medical physicist / Radiation oncologist / Research scientist (physics/engineering) / Other
5	Demographics	Years in current role *(optional)*	Single-select	<2 years / 2–5 years / 6–10 years / 11–20 years / >20 years
6	Clinical infrastructure	Which EBRT modalities/ techniques are routinely used at your institution? (Select all that apply)	Multi-select	2D conventional RT (2DRT) / 3D conformal RT (3DCRT) / Intensity-modulated RT (IMRT) / Volumetric modulated arc therapy (VMAT) / Image-guided RT (IGRT-CBCT) / Stereotactic body RT (SBRT) / Stereotactic radiosurgery (SRT/SRS) / Adaptive radiotherapy / MR-guided RT / Proton/particle therapy
7	Clinical infrastructure	Which treatment planning system (TPS) is used for EBRT? (Select all that apply)	Multi-select	Eclipse (Varian) / Monaco (Elekta) / Oncentra External Beam (Elekta) / Pinnacle (Philips) / RayStation (RaySearch) / Precision (Accuray) / Telecobalt TPS (Theratron/Bhabhatron/other cobalt) / Brainlab iPlan/ Elements / Other
8	Clinical infrastructure	Version of EBRT TPS *(optional)*	Free text	[Version number]
9	Clinical infrastructure	Is brachytherapy available at your institution?	Single-select	Yes / No
10	Clinical infrastructure	If brachytherapy is available, which types are in routine practice?	Multi-select	High dose rate (HDR) / Low dose rate (LDR) / Pulsed dose rate (PDR) / Not applicable
11	Clinical infrastructure	Which brachytherapy TPS is used?	Multi-select	BrachyVision (Varian) / Oncentra Brachy (Elekta) / Plato (Nucletron) / Other / Not applicable
12	Clinical infrastructure	Version of brachytherapy TPS *(optional)*	Free text	[Version number]

Continued

Supplementary Table S1. Full survey instrument. *Continued*

Item No.	Domain	Question text	Type	Response options
13	Radiobiological model usage	How often do you use radiobiological models for treatment planning or evaluation?	Single-select	Daily/routinely (>75% of cases) / Frequently (50%–75% of cases) / Occasionally (25%–50% of cases) / Rarely (<25% of cases) / Never
14	Radiobiological model usage	Which radiobiological models/ metrics do you use clinically or in research? (Select all that apply)	Multi-select	Biologically effective dose (BED) / Equivalent dose in 2 Gy fractions (EQD2) / Generalised equivalent uniform dose (gEUD) / TCP–Poisson statistical model / TCP–Logistic model / NTCP–Lyman–Kutcher–Burman (LKB) / NTCP–Critical volume model / NTCP–Relative seriality model / None
15	Radiobiological model usage	In which clinical contexts do you apply these models? (Select all that apply)	Multi-select	Fractionation scheme selection / Dose prescription adaptation / Re-irradiation planning / Plan evaluation/ audit / Plan optimisation / Toxicity risk prediction / Research only
16	Radiobiological model usage	Are radiobiological model parameters locally calibrated to your patient population?	Single-select	Yes / No / Not sure
17	Radiobiological model usage	Where do you obtain model parameters (e.g. α/β, TD50, n, m)? (Select all that apply)	Multi-select	Published literature values / National or international guidelines / TPS default values / Clinical trial protocols / Locally derived from institutional outcome data / Not applicable
18	Radiobiological model usage	Do you include radiobiological metrics in clinical documentation?	Single-select	Yes, routinely in treatment plans / Yes, in selected complex cases / No, but calculate for internal use / No, never document / Both options B and C
19	AI/ML implementation	What is the current status of AI/ML use in your radiotherapy workflow?	Single-select	Routine clinical use / Limited clinical implementation (pilot) / Currently in testing/validation phase / Planning to implement within 1 year / Planning to use within 2+ years / Not using and no plans to implement / Not available
20	AI/ML implementation	If using AI/ML, which applications are in use? (Select all that apply)	Multi-select	Auto-contouring/segmentation / Automated treatment planning / Plan optimisation / Image registration/ fusion / Patient-specific QA prediction / AI-based plan evaluation / Toxicity/outcome prediction / Adaptive RT decision support / Research only / None
21	AI/ML implementation	Which AI/ML methods or algorithms are used? (Select all that apply)	Multi-select	Deep learning (CNN, U-Net, etc.) / Machine learning (Random Forest, SVM, etc.) / Knowledge-based planning (KBP/RapidPlan) / Commercial AI solutions / In-house developed models / Open-source tools / Not applicable
22	AI/ML implementation	How are AI/ML models validated before clinical use?	Multi-select	Internal retrospective validation only / External dataset validation / Prospective clinical validation / Multi-institutional validation / Following vendor validation / No formal validation / Not applicable

Continued

Supplementary Table S1. Full survey instrument. *Continued*

Item No.	Domain	Question text	Type	Response options
23	AI/ML implementation	Do you monitor AI/ML model performance post-implementation?	Single-select	Yes, continuous monitoring with metrics / Yes, periodic audits / Yes, only when issues arise / No formal monitoring / Not applicable
24	Plan evaluation and barriers	Which implementation methods are used for radiobiological or AI/ML tools? (Select all that apply)	Multi-select	Built-in TPS functions / TPS scripting/API (Eclipse ESAPI, RayStation scripting, etc.) / Commercial standalone software / In-house developed code (Python/MATLAB/R) / Cloud-based solutions / Not applicable
25	Plan evaluation and barriers	Do you use any plan evaluation tool routinely or in research?	Multi-select grid	Physical evaluation: Yes/No; Radiobiological evaluation: Yes/No; ML/AI-capable evaluation: Yes/No
26	Plan evaluation and barriers	Which tools or software do you use for plan evaluation or radiobiological analysis? (Select all that apply)	Multi-select	In-built TPS evaluation modules (CI, HI, DVH-based metrics) / Spreadsheet or Excel-based calculations / Commercial radiobiological software (BioSuite, DVH Analyser, PlanIQ) / In-house developed MATLAB/Python/R scripts / Vendor plug-ins or macros within TPS / Open-source research tools (CERR, DREES, HART, RADBIOMOD) / No dedicated tool – manual or visual evaluation only
27	Plan evaluation and barriers	Please provide the name of available software/tools for radiobiological plan evaluation used at your facility (optional)	Free text	[Open response]
28	Plan evaluation and barriers	What are the main barriers to implementing radiobiological or AI/ML-based planning tools? (Select all that apply)	Multi-select	Limited software access or licensing costs / Inadequate TPS capabilities or infrastructure / Lack of clinical validation or guidelines / Limited awareness of AI/ML approaches / Insufficient staff expertise or training / Limited funding or financial resources / Lack of institutional support / Poor data quality or missing datasets / Regulatory or ethical approval delays / Weak supporting IT professionals
29	Plan evaluation and barriers	Which type(s) of plan evaluation do you perform?	Multi-select	Physical evaluation / Radiobiological evaluation / ML/AI-capable or supported evaluation
30	Training, research and future priorities	Have you received formal training in the following areas? (Select all that apply)	Multi-select	Radiobiological modelling – formal course / Radiobiological modelling – workshop/conference / AI/ML in radiotherapy – online course / AI/ML in radiotherapy – workshop/conference / Advanced TPS features / Programming for medical physics / None of the above
31	Training, research and future priorities	What training would be most valuable? (Select top 3 preferences)	Multi-select (max 3)	Advanced radiobiological modelling / AI/ML fundamentals / AI/ML implementation in radiotherapy / Programming skills (Python/MATLAB) / Clinical validation methods / Regulatory and ethics of AI

Continued

Supplementary Table S1. Full survey instrument. *Continued*

Item No.	Domain	Question text	Type	Response options
32	Training, research and future priorities	Have you published peer-reviewed articles on radiobiological models or AI/ML in radiotherapy?	Single-select	No publications / Yes, 1–2 publications / Yes, 3–5 publications / Yes, >5 publications
33	Training, research and future priorities	Do you share research data, code or models publicly?	Single-select	Yes, routinely (open science) / Yes, upon request / No, institutional restrictions / No, other reasons / Planning to share / Not applicable
34	Training, research and future priorities	Rank the following in order of institutional priority (1 = highest, 5 = lowest): Clinical implementation of TCP/NTCP	Ranking (1–5)	1 / 2 / 3 / 4 / 5
35	Training, research and future priorities	Rank: AI-based auto-contouring	Ranking (1–5)	1 / 2 / 3 / 4 / 5
36	Training, research and future priorities	Rank: Automated treatment planning	Ranking (1–5)	1 / 2 / 3 / 4 / 5
37	Training, research and future priorities	Rank: Outcome prediction models	Ranking (1–5)	1 / 2 / 3 / 4 / 5
38	Training, research and future priorities	Rank: Adaptive radiotherapy workflows	Ranking (1–5)	1 / 2 / 3 / 4 / 5
39	Training, research and future priorities	Would you be interested in participating in: (Select all that apply)	Multi-select	Multi-institutional validation studies / Data sharing consortiums / Collaborative model development / Training/workshop participation / Beta testing new tools
40	Training, research and future priorities	Additional comments, suggestions, or insights (optional)	Free text	[Open response]
—	Post-survey	How did you learn about this survey?	Single-select	MEDPHYS mailing list / Professional society/ organisation email / Colleague recommendation / Institutional communication / Conference/workshop / Journal/newsletter / Social media
—	Post-survey	How would you rate this survey experience?	Likert 1–5	1 (Poor) – 5 (Excellent)
—	Post-survey	Would you like to receive a summary of results?	Single-select	Yes, please send me a summary / No, I prefer not to receive follow-up
—	Post-survey	Email address (optional, for follow-up only)	Free text	[Email address – not analysed]

Items 34–38 form a single 5-item ranking question. Post-survey items (discovery channel, rating, follow-up) were collected for quality assurance and dissemination purposes and were not included in the primary analysis

Supplementary Table S2. Data quality assurance results.

QA check	Criterion / Check	Finding	Action
Completeness	Demographics / infrastructure (100% complete)	42/42	No action required
	RB model frequency and calibration (95.2%)	2 skipped	Reported on *N* = 42 with explicit 'Other' and 'Not stated' categories
	AI/ML implementation status (92.9%); AI/ML applications, validation and monitoring (64.3%–66.7%; items conditional on current AI/ML use)	3 skipped	Reported on *N* = 42; conditional items identified in the figure legends
	Barriers (76.2%)	10 skipped	Reported on *N* = 42 with a 'Not stated' row (*n* = 10)
Internal consistency	RB model domain: selected 'Never use' but named specific models	4/42 (9.5%)	Retained; reflects awareness–application gap
	AI/ML domain: indicated no AI use but named specific applications	4/42 (9.5%)	Retained; same interpretation as above
Plausibility	VMAT availability versus national benchmark (88%)	88.1% – Concordant	No action
	Eclipse TPS dominance versus market share data	50.0% – Concordant	No action
Discordance	Overall discordance rate across both domains	9.5% per domain	Reported transparently; all responses retained

A four-step QA protocol was applied: (i) completeness analysis; (ii) internal consistency (cross-referencing related response items); (iii) plausibility verification against published literature benchmarks and (iv) transparent reporting of discordance patterns. Discordant responses were retained and reported as data quality indicators

Supplementary Table S3. Exploratory stratification by profession and institution type.

Panel A – by profession.			
Metric	**Medical physicist (*n* = 33)**	**Radiation oncologist (*n* = 8)**	**All (*N* = 42)**
Confirmed local calibration	3 (9.1%)	2 (25.0%)	6 (14.3%)
RB model for plan evaluation	10 (30.3%)	5 (62.5%)	16 (38.1%)
Routine AI/ML clinical use	8 (24.2%)	0 (0.0%)	8 (19.0%)

One research scientist (*n* = 1) is included in the 'All' column but omitted from the two profession columns for clarity

Panel B – by institution type.

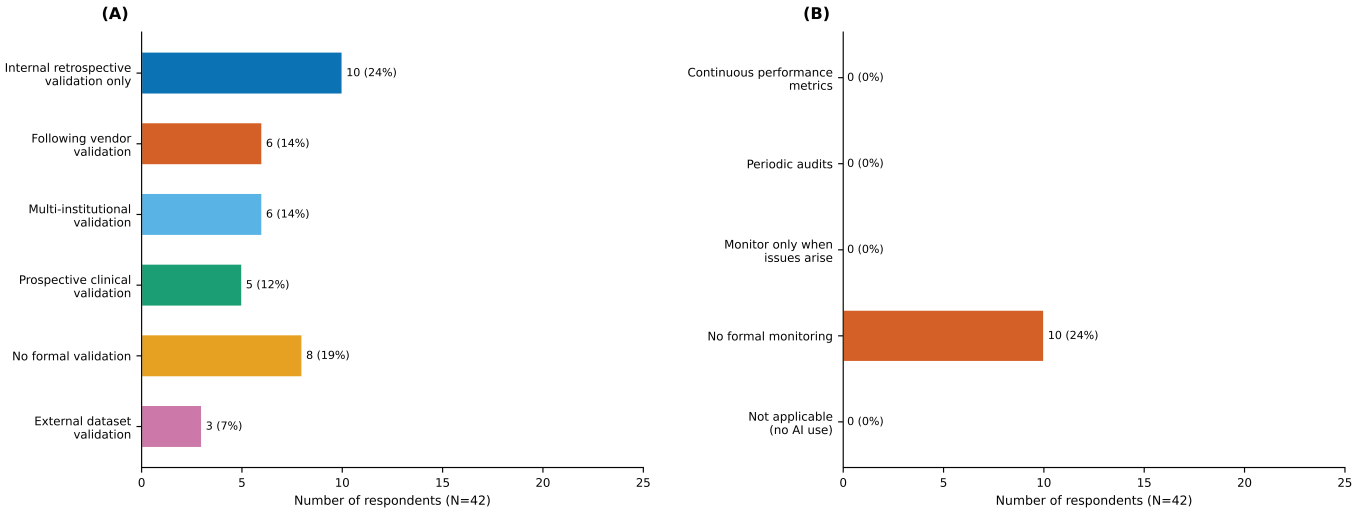
Metric	**Academic/teaching (*n* = 22)**	**Non-academic (*n* = 19)**
Confirmed local calibration	6 (27.3%)	0 (0.0%)
RB model for plan evaluation	11 (50.0%)	5 (26.3%)
Routine AI/ML clinical use	3 (13.6%)	5 (26.3%)

Notably, all six respondents confirming local calibration practised at academic/teaching institutions. Patterns are unadjusted and hypothesis-generating. Descriptive only; no formal statistical testing was performed, given the small strata. Denominators are subgroup sizes. 'Academic/teaching' combines academic hospitals, medical colleges/universities and cancer research/teaching centres (*n* = 22); 'Non-academic' combines private, government, community and other centres (*n* = 19); one respondent did not state institution type. No India–international subgroup comparison is presented. With only 12 respondents practising outside India, across nine countries, the registered protocol's threshold of 20 responding centres per subcontinental region for quantitative regional synthesis was not met, and the protocol specifies that regions below that threshold be described narratively only

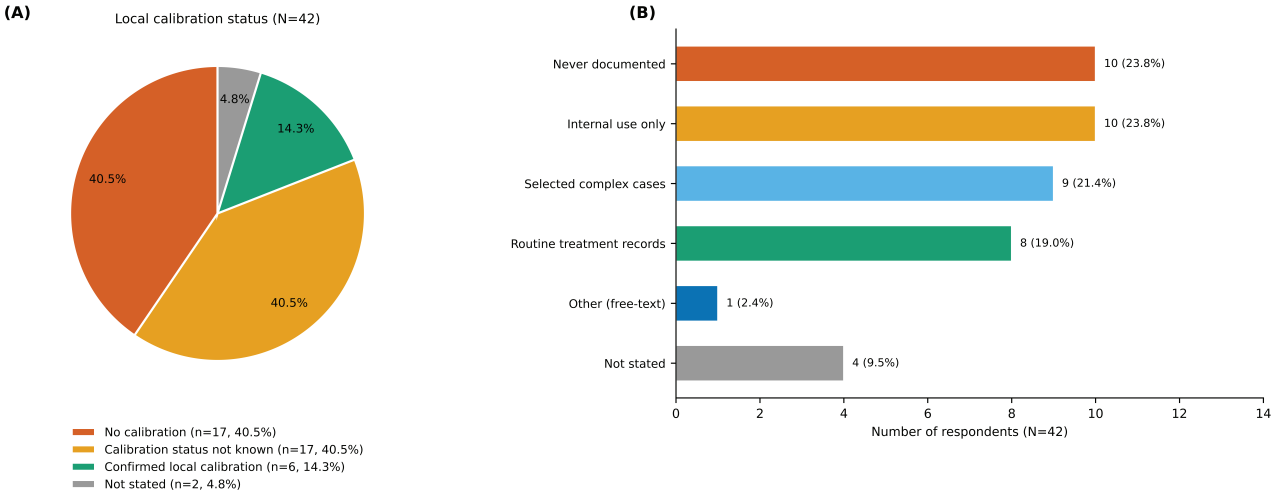
Supplementary Table S4. External validation of key survey findings.

Survey finding	Literature benchmark	Concordance	Notes
VMAT availability (88.1%)	India national survey: 88% IMRT/VMAT [25]	Concordant	–
Eclipse most frequently reported TPS (50.0% of 52 selections)	Consistent with national RT equipment surveys [29] and Varian market share data	Concordant	–
BED/EQD2 most recognised (>70%)	QUANTEC/HyTEC guideline integration [30,31]	Concordant	–
TCP/NTCP low adoption (<35%)	Limited real-world use confirmed [14,15]	Concordant	NL exception [11,12]
Auto-contouring leading AI (50.0%)	AAPM–ESTRO maturity hierarchy [20]	Concordant	–
Low plan evaluation adoption (38.1%)	TG-166 characterisation of limited real-world use [16]	Concordant	Descriptive estimate from this sample
Calibration practice (confirmed 14.3%; no calibration 40.5%; status not known 40.5%)	No direct published comparator	Novel finding	Descriptive estimate from this sample
Publication activity (83.3% with no publications)	No direct published comparator	Novel finding	Descriptive estimate from this sample

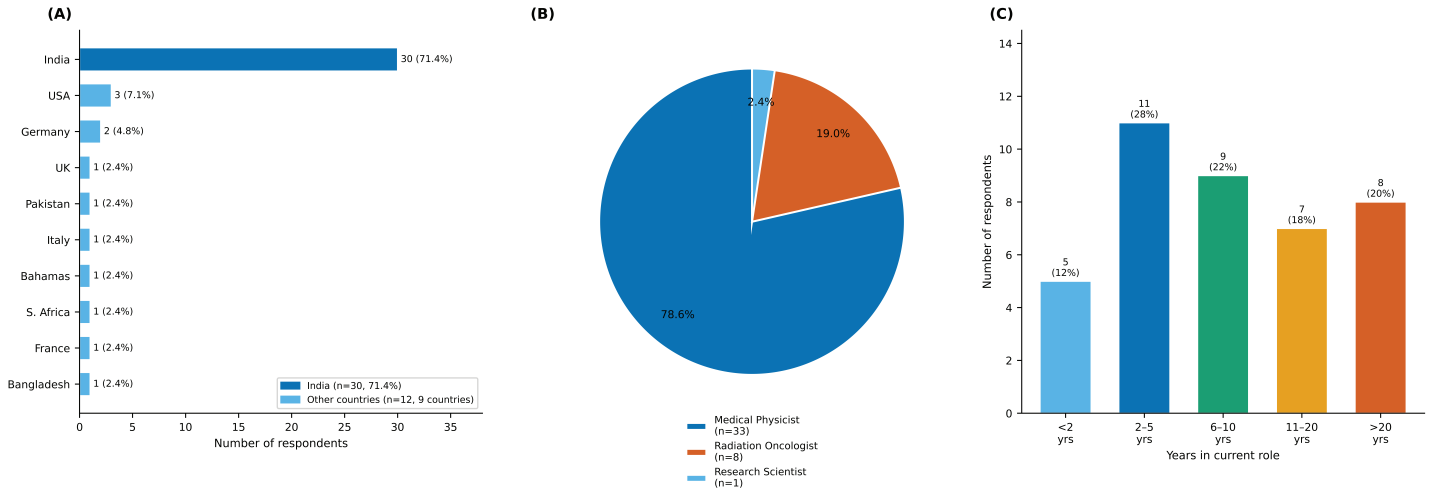
Key survey metrics were cross-referenced with published benchmarks to assess plausibility and external validity. Citation numbers in this table refer to the reference list of the main manuscript



Supplementary Figure S1. AI/ML validation and monitoring practices (*N* = 42; multiple selections permitted; percentages calculated on the full sample). (A) Validation approaches used for AI/ML systems (answered by 27 respondents). (B) Post-implementation monitoring practices (answered by 28 respondents); 11.9% reported prospective clinical validation, and 23.8% reported no formal monitoring programme.



Supplementary Figure S2. Radiobiological model calibration and documentation practices (*N* = 42). (A) Local parameter calibration status, shown as four mutually exclusive categories on the full sample: confirmed local calibration (Yes, *n* = 6, 14.3%), no calibration (No, *n* = 17, 40.5%), calibration status not known ('Not sure', *n* = 17, 40.5%) and not stated (*n* = 2, 4.8%). The 'not sure' responses are reported separately from 'no' throughout, because uncertainty about institutional practice is not evidence that calibration is absent. (B) Documentation of radiobiological calculations in clinical records (*N* = 42), including free-text and unanswered responses.



Supplementary Figure S3. Demographic detail of survey respondents (*N* = 42). (A) Country of practice (India in blue, all other countries in sky blue). (B) Professional role distribution. (C) Years of experience in current role; two respondents did not state their experience and percentages are calculated on the full sample.