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Artificial intelligence in radiation therapy treatment planning: A discrete choice experiment

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artificial intelligence, DCE, discrete choice experiment, preferences, radiation oncology professionals, radiation therapy planning, willingness-to-save time

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Abstract

Introduction: The application of artificial intelligence (AI) in radiation therapy holds promise for addressing challenges, such as healthcare staff shortages, increased efficiency and treatment planning variations. Increased AI adoption has the potential to standardise treatment protocols, enhance quality, improve patient outcomes, and reduce costs. However, drawbacks include impacts on employment and algorithmic biases, making it crucial to navigate trade-offs. A discrete choice experiment (DCE) was undertaken to examine the AI-related characteristics radiation oncology professionals think are most important for adoption in radiation therapy treatment planning. **Methods:** Radiation oncology professionals completed an online discrete choice experiment to express their preferences about AI systems for radiation therapy planning which were described by five attributes, each with 2–4 levels: accuracy, automation, exploratory ability, compatibility with other systems and impact on workload. The survey also included questions about attitudes to AI. Choices were modelled using mixed logit regression. **Results:** The survey was completed by 82 respondents. The results showed they preferred AI systems that offer the largest time saving, and that provide explanations of the AI reasoning (both in-depth and basic). They also favoured systems that provide improved contouring precision compared with manual systems. Respondents emphasised the importance of AI systems being cost-effective, while also recognising AI's impact on professional roles, responsibilities, and service delivery. **Conclusions:** This study provides important information about radiation oncology professionals' priorities for AI in treatment planning. The findings from this study can be used to inform future research on economic evaluations and management perspectives of AI-driven technologies in radiation therapy.

Introduction

As the population ages, the demand for high quality cancer services increases. Cancer cases are expected to increase by 22% between 2021 and 2031, greater than the rate of population increase (15%).[1] The Australian Institute of Health and Welfare (AIHW) estimates 1.9 million cases of cancer will be diagnosed between 2024 and 2033.[2] Radiation therapy (RT) treatment is one of the prime modalities used in oncology and it is an important part of cancer treatment for about 50% of cancer patients.[3] The increasing demand for RT also drives the need for improvement in RT efficiency to meet this demand.

Artificial intelligence (AI) is transforming numerous medical fields and its application in RT has the potential to address the challenges faced by the field such as healthcare staff shortages, inefficiency and variation in treatment planning and delivery.[4] AI has the ability to manage very complex, high-dimensional, and multifactorial problems that are commonly encountered in the field of RT and medical imaging.[5] AI systems have been shown to be accurate for tasks that are time-consuming and which demand focus, such as identifying patterns and abnormalities in medical images.[6]

There is increasing research showing that AI achieves superior accuracy compared to processes primarily reliant on human input. AI has been shown to be more effective at analysing the medical images to detect lung cancer, liver cancer,[7] and breast cancer[8] compared with healthcare professionals (HCPs). Results from a Swedish randomised controlled trial (RCT) comparing AI with standard screen reading following mammography of 80,000 women found that cancer detection rates were 20% higher in women whose mammograms were read by a radiologist using AI compared with women whose mammograms were read by two radiologists without any AI intervention. In addition, the results showed the AI supported screen-reading procedure enabled a 44·3% reduction in the screen-reading workload.[8] Results from recent research exploring the use of AI in organ delineations on computed tomography (CT) scans for radiation treatment planning in prostate cancer showed that automated delineations of the prostate and organs at risk (OAR) can be successfully performed by AI compared with manual methods.[9] AI in auto-contouring compared with a human practitioner shows improved performance in terms of precision, differences in dose distribution, and time consumption.[10,11]

Time savings offered by AI systems may increase patient throughput and streamline workflows, but it is essential to balance these efficiency gains with maintaining high quality standards.[12] Application of AI in clinical settings requires that AI models are trained on high-quality, relevant data to ensure reliability of the recommendations provided by AI and to ensure patients' safety. Concerns have been raised that AI algorithms may be developed using data sets that are not representative of the individuals that the system is designed to serve, and that inaccurate or incomplete data may lead to discrimination and medical errors.[13] Previous research has found that AI-models do not always perform well across all demographic groups, with women and people of colour most commonly discriminated against.[14] To ensure the responsible and equitable deployment of AI systems requires understanding the sources and quality of data informing them. The AI algorithms may lack interpretability or transparency in their decision making processes, the phenomenon referred to as being a "black box".[15] Lack of understanding of the AI systems decisions may lead to issues with both validation and clinical oversight. It may also affect the doctor-patient relationship as clinicians may be unable to explain decisions made by AI algorithms to their patients.[15] Making sure that AI systems can explain their decisions is also important for building trust among HCPs, mitigating concerns about algorithmic bias and to account for potential liability issues. Concerns about who is accountable for decisions made with AI assistance remain significant, emphasising the need for development of clear and transparent AI processes in clinical settings.

Due to the evolving nature of AI systems, it is crucial to gain a deeper understanding of the perceptions and needs of stakeholders affected by these systems, including healthcare providers, patients, and caregivers. This understanding is essential to ensure the successful integration of AI into healthcare systems.[16] A recent survey suggested that radiation oncology professionals generally feel optimistic about the application of AI in RT and the impact AI will have on their role.[17] However, the trade-offs between specific features of AI, such as accuracy versus explainability (transparency) of the system's underlying reasoning, and security of patient information versus performance gains attained through enhanced access to patient data may be necessary.[18] Health preference research makes it possible to investigate and quantify these preferences and trade-offs to better understand the attitudes of the stakeholders such as patients and health care service providers. While there is some research on preferences for AI integration in healthcare,[17,19–23] studies utilising stated preference approaches remain scarce. This study seeks to fill this gap by examining preferences and attitudes towards the adoption of AI in RT treatment planning using a discrete choice experiment (DCE), which is a quantitative stated preference method. DCE is a method of eliciting stated preferences from respondents through a structured survey that presents respondents with a series of hypothetical choice tasks presenting multiple characteristics (attributes) to simulate realistic choice scenarios.[24] Choice experiments are widely used in transport economics, environmental economics, marketing, and health economics.[25–29] DCEs are increasingly popular in evaluation of digital health technologies across a wide range of health-related concerns.[24] This research aims to determine the features of the AI systems that Australian radiation oncology professionals would value most, which can then inform decision makers about ways to improve the provision of RT treatment based on AI-systems in Australia.

Methods

We designed a DCE to identify the features of AI systems and their impact on RT that are most important to users. A DCE was chosen as the most appropriate method for the research question because there is no established market revealing preferences of HCPs who are involved in RT treatment planning, due to limited information on the relatively new market segment. The DCE design allows the researcher to create a choice scenario in a contingent yet realistic market to assess preferences for different features of AI.

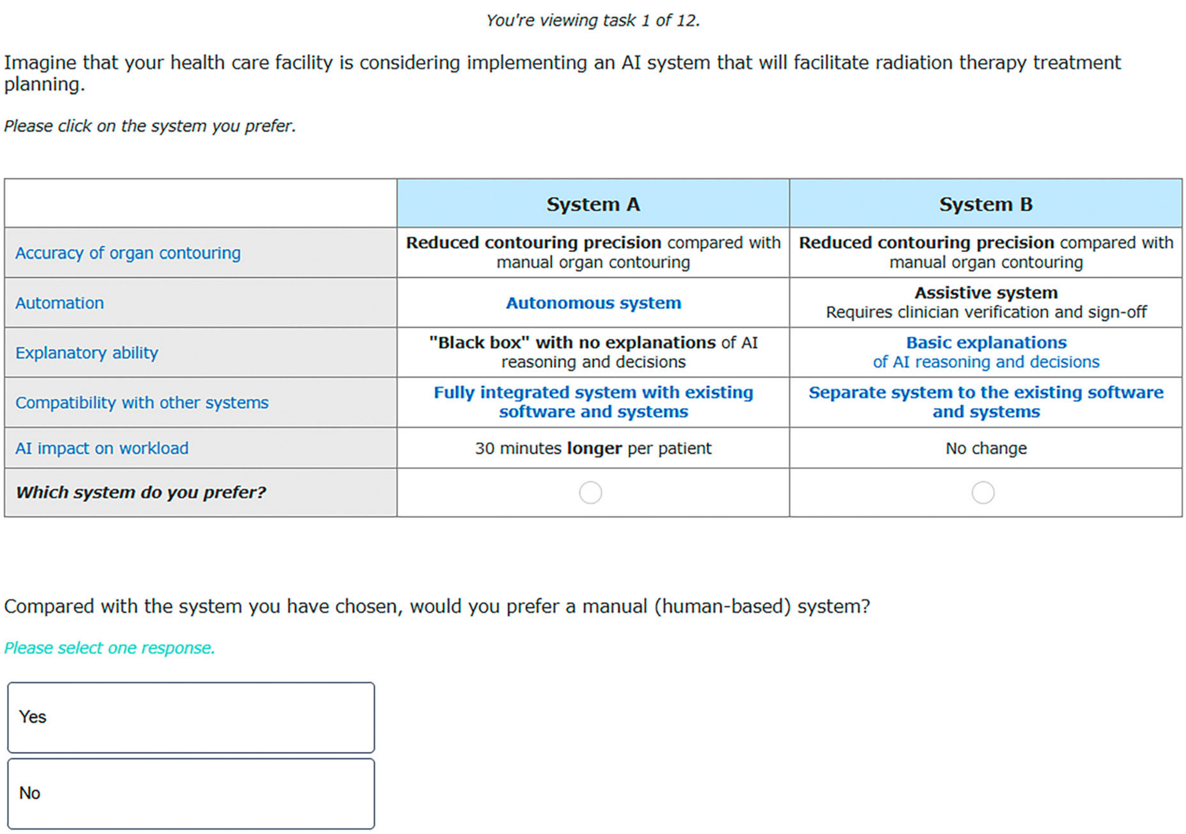
The survey instrument was developed using the steps recommended by the International Society for Pharmacoeconomics and Outcomes Research (ISPOR) taskforce.[30] The DCE tasks were created and refined in stages based on both qualitative and quantitative methods. Vignettes, attribute descriptions, and levels were developed using existing literature and consultations with HCPs with expertise in AI. The vignette, attributes and levels descriptions were refined based on detailed feedback from researchers with experience in implementation of DCEs, and review by HCPs to ensure descriptions were comprehensive and accurate.

The survey included four sections: (1) Background information; (2) The DCE which included 12 tasks per respondent; (3) debriefing questions and (4) questions about attitudes and opinions to adoption of AI in RT planning. The survey structure is presented in Fig. 1 in the Appendix S1.

Figure 1 presents an example of the DCE choice task as presented to respondents. Each choice task consisted of a vignette describing the circumstances in which the respondent is asked to imagine that their health care facility is considering implementing an AI system. Two different systems are described in terms of their features: accuracy, automation, explainability, compatibility and impact on workload (Table 1). Respondents were asked to compare the options based on the attributes described and select their more preferred option. They were then asked if they would prefer the system they chose or a manual system.

The AI systems accuracy and explainability were assigned three levels. A four-level attribute described the impact of AI on workload described as time needed for generating of RT plans (range from 30 min longer to 60 min saved per patient). A two-level attribute described automation and AI compatibility with other systems.

The designed experiment contained 36 choice tasks which were divided into three versions, each with 12 choice sets. The initial D-optimal design was constructed using idefix[31] to select the choice options to be included in the experiment to allow for estimation of the main


You're viewing task 1 of 12.

Imagine that your health care facility is considering implementing an AI system that will facilitate radiation therapy treatment planning.

Please click on the system you prefer.

	System A	System B
Accuracy of organ contouring	**Reduced contouring precision** compared with manual organ contouring	**Reduced contouring precision** compared with manual organ contouring
Automation	**Autonomous system**	**Assistive system** Requires clinician verification and sign-off
Explanatory ability	**"Black box" with no explanations** of AI reasoning and decisions	**Basic explanations** of AI reasoning and decisions
Compatibility with other systems	**Fully integrated system with existing software and systems**	**Separate system to the existing software and systems**
AI impact on workload	30 minutes **longer** per patient	No change
Which system do you prefer?	○	○

Compared with the system you have chosen, would you prefer a manual (human-based) system?

Please select one response.

Yes

No

Figure 1. Example of a DCE choice task.

Table 1. Overview of attributes and levels; DCE– radiation oncology professionals involved in RT treatment planning and delivery.

Attributes	Levels	Definition
Accuracy of organ contouring	1. Reduced contouring precision compared with manual organ contouring 2. Same contouring precision as manual organ contouring 3. Improved contouring precision compared with manual organ contouring	Degree of precision and accuracy of the AI system output compared to manually contoured healthy organs
Automation	1. Assistive system: Requires clinician verification and sign-off 2. Autonomous system: AI system operates without the need for human intervention. It can make decision and execute tasks independently	The use of AI algorithms to perform repetitive and manual activities typically carried out by humans with minimal or no human intervention (e.g. automation of outlining healthy organs, Quality Assurance (QA)of human-driven processes).
Explanatory ability	1. "Black box" with no explanations of AI reasoning and decisions 2. Basic explanations of AI reasoning and decisions: Providing a comprehensive summary of AI reasoning but no explanation of its algorithm and data sources it used. 3. In-depth explanations of AI reasoning and decisions: AI system provides a comprehensive summary of AI reasoning, the algorithms used, and the data sources it referenced to generate its solution.	The ability of AI to provide understandable, transparent, and trustworthy explanations for its decisions or actions.
Compatibility with other systems	1. Separate system to the existing software and systems: Requires exporting/importing of data during the planning process. 2. Fully integrated system with existing software and systems: No need to export or import data during the planning process.	Different approaches to connecting and integrating AI with other systems or applications.
AI impact on workload	1. 30 min longer per patient 2. No change 3. 30 min saved per patient 4. 60 min saved per patient	The impact of AI on the time required for generating treatment plans (dosimetry) compared with a predominantly human-based system

effect for each attribute (accuracy, automation, explainability, compatibility and impact on workload) using a multinomial logit (MNL) model. All variables were dummy coded.

The design was tested with simulations prior to implementation. The simulations were conducted based on zero (utility neutral) priors, with 1000 iterations, each for 25 respondents per version. The simulations yielded small standard errors and ranges for each estimated parameter, demonstrating that the design was robust with 75 respondents in total (25 per version). The model can be fitted to the results from each version independently if required.

The survey was implemented in a sample of HCPs working in Australia. Eligibility criteria included HCPs involved in RT planning, such as radiation therapists, radiation oncologists, and medical physicists. Respondents were recruited using a range of approaches, including through radiation oncology professional associations, including The Australian Society of Medical Imaging and Radiation Therapy (ASMIRT) and its AI special interest group and Educators group for radiation oncology HCPs in Australia. Information about the study and a link to the survey was disseminated at the Trans-Tasmanian Radiation Oncology Group Annual Scientific Meeting (TROG ASM) (Newcastle, 12-15th March 2024) and ASMIRT conference (Darwin, 8–12 May 2024). In addition, individual emails ($N = 277$) were sent to HCPs involved in RT planning. Respondents were invited to participate via an email link. Data were collected between 26 February 2024 and 31 May 2024. This study was approved by the University of Technology Health Research Ethics Committee, ETH21-6090, 10 November 2023.

Model specification and analysis

Data were analysed in R Studio 2024.[32] Descriptive statistics were used to summarise the characteristics of the overall sample. A MNL model was originally fitted to the data. The marginal willingness to save time was estimated using coefficients from the MNL model using the impact on workload variable to calculate a marginal rate of substation (MRS), which represents the change in time saving that would compensate for a change in another attribute. Relative attribute importance was calculated by dividing the range of marginal utilities of the respective attribute by the sum of all attribute ranges. Two approaches were adopted to account for heterogeneity: mixed logit (MIXL) and latent class (LC) modelling. Mixed logit modelling generalises the MNL model by allowing the preference or taste parameters to be different for each individual.[28] The MIXL model was estimated using the GMNL package[33] in R Studio 2024. All variables were dummy coded, and each model was simulated with 5000 draws. The base level for each variable was used to compare the estimated coefficients of the other levels.

Another approach to explore preference heterogeneity in the data is to use a LC model.[24] LC analysis is used to identify subgroups within a population based on individuals' responses to various observed variables. It assumes that these subgroups, or LCes, explain the pattern of responses observed in the data. The LC model was estimated with the GMNL package[33] in R studio 2024. Given the small sample size, specific characteristics that are likely to impact on preferences were not identified. To evaluate model fit, log likelihood, Akaike information Criterion (AIC) and Bayesian Information Criterion (BIC) were determined.[34] The number of classes to include was informed by the model with the lowest BIC across models with from 2 to 4 classes.

Results

There were 137 respondents who started the survey and gave informed consent and provided background information. There were 112 respondents who initiated the DCE and who were allocated to one of three versions of the DCE survey, of whom 82 (73%) finished all choice tasks. The drop out was not significantly different across the survey versions. The majority of DCE respondents were radiation therapists (52%). No respondents were excluded due to the small sample size, as it was considered important to capture the preferences of all professionals involved in the RT planning process. Respondents were predominantly HCPs who received their training in Australia (91%) and who were working in the public sector (75%), with an average professional experience of 15 years. Most of the respondents had prior experience with AI. The average size of work facilities was 14 persons. The respondents were involved in most of the planning activities, with more than half being involved in organ at risk contouring, plan evaluation and quality assurance (Table 2).

DCE results

The estimation of the mixed logit model yielded significant effects at 1% significance level for all levels of all attributes (Table 3). The magnitude of each standard deviation (for 6 out of 9 attribute levels) is similar to its corresponding coefficient, indicating that there is heterogeneity in the sample, that is, variability in individual respondents' preferences exists. The estimated standard deviations for an improved accuracy of an AI system and time saved per patients during treatment planning were not statistically significant, indicating no evidence of preference heterogeneity within the sample for these attributes and levels.

The mixed logit results are also illustrated in Fig. 2, which shows the point estimate and the corresponding 95% confidence intervals for each attribute level. The results show the highest preference is for an AI-system that reduces workload (time saved), followed by an AI

Table 2. Respondents characteristics.

Characteristics	Frequency (N = 82)	Percentage
Radiation therapist	43	52
Medical physicist	24	29
Radiation oncologist	9	11
Other[a]	6	7
Radiographer	1	1
Branch manager	1	1
Lecturer	1	1
Researcher (RT)	2	2
Student	1	1
Location of training		
Australia	75	91
New Zealand	3	4
Other	4	5
UK	4	5
Work settings		
Public	61	74
Private	7	9
Both	13	16
Years of experience	15 (9)	NA
Mean (SD)	1,34	
Min, max		
Aspects of RT involved		
Patient positioning	36	44
Image registration and reconstruction	36	44
Image simulation	29	35
Image fusion	41	50
Organ at risk (OAR) contouring	46	56
Target contouring	23	28
Plan set up	32	39
Plan optimisation	42	51
Plan evaluation	57	69
Quality assurance	57	69
Other	9	11
Size of workplace (N, SD)	14 (14)	NA
Currently using AI at work		
Yes	44	54
No	29	35
Don't know	8	10

[a]The average number of years of experience among "other" professionals (n = 6) was 12 (SD 12) range 3–30.

Table 3. Results of the DCE responses, analysed using mixed logit model.

Attributes	Levels	Mean (SE)	SD (SE)
Accuracy (Base = Same as current)	Reduced	−3.58 (0.70)***	2.34 (0.56)***
	Improved	1.15 (0.24)***	0.09 (0.94)
Automation (Base = Assistive)	Autonomous	−0.84 (0.25)***	1.55 (0.33)***
Explainability (Base = “Black box”)	Basic explanations	1.46 (0.29)***	0.94 (0.38)*
	In-depth explanations	1.46 (0.35)***	1.74 (0.43)***
Compatibility (Base = Separate systems)	Fully integrated systems	0.97 (0.25)***	1.14 (0.30)***
Impact on workload	30 min longer	−1.14 (0.34)***	1.36 (0.45)**
(Base = No change)	30 min saved	1.16 (0.30)***	0.49 (0.73)
	60 min saved	1.63 (0.35)***	0.66 (0.48)
Number of draws	5000		
Sample (observations)	984		
AIC	956.90		
BIC	868.85		
LL	−416.43		

Note: ***$p < 0.001$, **$p < 0.01$, $p < 0.05$.
Abbreviations: AIC, Akaike information criterion; BIC, Bayesian information criterion; LL, log-likelihood; SD, standard deviation; SE, standard error.

system with an ability to provide explanations (whether basic or in-depth) (Fig. 2). The results showed that negative utility associated with AI systems with reduced accuracy and fully autonomous systems. The results from the DCE were consistent with the responses to questions about attribute importance that revealed that AI accuracy and impact on workload were the most frequently considered attributes when choosing between the AI systems (Fig. 2; Appendix S1).

The results from LC model are presented in Table 4. Based on the BIC estimates the best fit was the model with two classes. Class 1 (share, 74%) prefers improved accuracy ($p < 0.001$), an AI system that provides basic explanations for its decisions ($p < 0.001$), that is fully integrated with the existing systems ($p < 0.001$) and that offers the biggest time saving (60 min) ($p < 0.001$). Class 2 (share, 26%) strongly prefers assistive AI systems ($p < 0.001$) and AI systems that are fully integrated with the existing systems ($p < 0.001$). However, class 2 prefers in-depth explanations for AI-decisions ($p < 0.001$) rather than basic explanations. Preferences estimates for the impact on workload for class 2 showed that AI systems that require an additional 30 min for treatment plan preparation have statistically significant negative impact on workload. In contrast, time savings of 30 and 60 min did not show statistically significant effect for class 2 (Table 4).

The marginal willingness-to-save (WTS) time values for each attribute level are presented in Table 5. These results can be interpreted as the amount of time saving that would be required to compensate for different features of the AI system. For an AI system that had reduced accuracy, a time saving of 111 min compared with a human based system would be required. To compensate and for a system that was autonomous, a time saving of 32 min would be required (compared with a system that was assistive). For an AI system that has an improved accuracy it could take an additional 42 min. Compared with a “black box” type of AI systems, a system that could provide basic and in-depth explanations can take an hour longer per patient (Table 5).

Regarding respondents’ attitudes and opinions about the adoption of AI in healthcare and RT, the primary concern was the potential impact of AI algorithmic biases on healthcare delivery across different groups. Respondents were divided on whether AI would lead to workforce displacement but were generally enthusiastic about using AI to improve RT delivery and enhance the diversity of skill sets within their professional teams. They believed that implementing AI in RT treatment planning was unlikely to diminish human connection in patient care. However, there was no clear support for including information about the use of AI in informed consent for patients (Table 1; Appendix S1). Regarding the survey follow-up questions, the majority of respondents did not find the tasks difficult and considered all features for each system option. However, 22% of respondents reported difficulty in distinguishing between the presented options. The results of sensitivity analysis after excluding these respondents remained consistent with the base case results (Table 2; Appendix S1).

Discussion

The study investigated the preferences of radiation oncology professionals regarding the use of AI in RT planning, focusing on specific features of AI systems. The results of this DCE indicated that the most important features for respondents were the AI system’s ability to save time in treatment planning, provide basic explanations for its decisions, and offer improved accuracy compared to human-based systems. Respondents expressed a preference for AI systems that are assistive rather than fully autonomous and those that are fully integrated into existing software and systems.

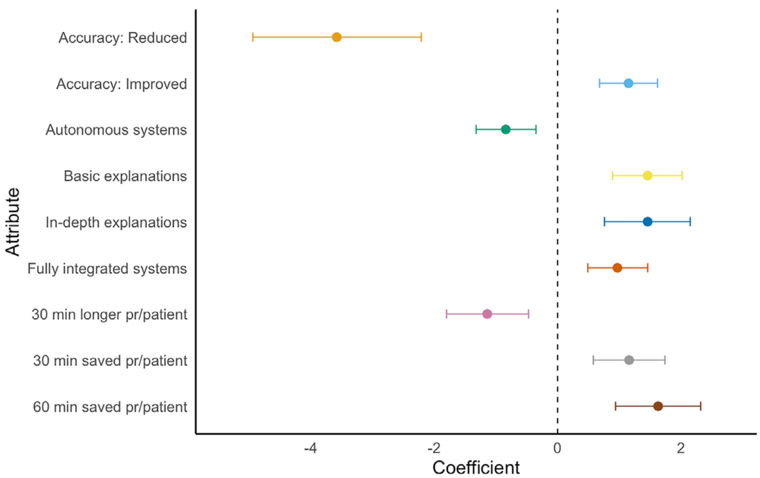


Figure 2. A forest plot of results from DCE based on mixed logit model: estimated effect and confidence intervals.

Table 4. Results from a latent class logit model with 2 classes: class specific parameters and model fit statistics.

Attributes	Levels	Class 1 (Coeff, SE)	Class 2 (Coeff, SE)
Accuracy (Base = Same as current)	Reduced	−2.33 (0.27)***	−0.84 (0.42)*
	Improved	0.86 (0.17)***	0.56 (0.29)*
Automation (Base = Assistive)	Autonomous	−0.17 (0.13)	−1.20 (0.28)***
Explainability (Base = "Black box")	Basic explanations	0.69 (0.16)***	1.42 (0.35)***
	In-depth explanations	0.31 (0.20)	2.36 (0.50)***
Compatibility (Base = Separate systems)	Fully integrated systems	0.44 (0.13)***	0.97 (0.26)***
Impact on workload (Base = No change)	30 min longer	−0.73 (0.20)***	−0.48 (0.36)***
	30 min saved	1.07 (0.23)***	−0.05 (0.33)
	60 min saved	1.27 (0.22)***	0.36 (0.32)
Average class share		0.74	0.26
Constant, SE		Base class	−1.07 (0.09)
Observations	984		
LL	−421.76		
AIC	881.51		
BIC	974.46		

Note: ***$p < 0.001$, *$p < 0.05$.
Abbreviations: AIC, akaike information criterion; BIC, Bayesian information criterion; LL, log-likelihood; SD, standard deviation.

Table 5. Willingness-to-save time results.

Attributes	Levels	Mean, min (SE)
Accuracy (Base = Same as current)	Reduced	−111 (15.22)***
	Improved	43 (9.30)***
Automation (Base = Assistive)	Autonomous	−32 (6.95)***
Explainability (Base = "Black box")	Basic explanations	59 (10.29)***
	In-depth explanations	56 (10.50)***
Compatibility (Base = Separate systems)	Fully integrated systems	38 (7.15)***

Note: ***$p < 0.001$.
Abbreviations: SE, standard error; WTS, willingness-to-save.

A previous DCE survey of German radiologists found that development, funding, and research regarding AI tools should consider providers' preferences for features of immediate every day and economic relevance like time savings to optimise adoption.[35] The results of the current DCE suggest that radiation oncology HCPs may be more interested in AI tools that have positive impact on the specific activities involved in RT treatment planning.

The preference for basic AI system explanations among respondents may reflect a desire for access to systems that provide a balanced level of information about AI decisions. Such systems should offer sufficient detail to ensure understanding of the AI process while being feasible enough to improve the effectiveness of their work and communication with patients. Respondents' preference for the time savings offered by AI systems is an important finding of this study, considering the high volume of patients in this field, and the treatment plans that radiation therapists are required to generate daily.[36] Previous research showed that auto-contouring was one of the most popular AI-supported applications.[37] Respondents' prior knowledge about the specific applications of AI may have informed their preferences for the improved accuracy.[38] The respondents were willing to trade-off a longer time for treatment planning for a potentials benefit (i.e. improved accuracy, in-depth explanations and systems that are fully integrated with the existing systems).

The MXL analyses demonstrate that there is variability in the preferences about certain features of AI systems, particularly the reduction in AI accuracy, fully autonomous AI systems, AI explainability (both basic and in-depth), compatibility with the existing systems and negative AI impact on workload. This heterogeneity of preference was further explored in the latent class modelling, which revealed two distinct classes with differences in the preferences observed with respect to automation and AI ability to provide in-depth explanations and impact of AI on workload, resulting in time saving.

Although most respondents in this DCE were enthusiastic about the use of AI in their clinical settings and its potential to improve RT planning, concerns about algorithmic bias and its potential to exacerbate health inequalities were noted. However, the lack of uniform attitudes towards AI in healthcare reflects the complex and multidimensional nature of AI technology.[17] The average workplace size, consisting of 14 professionals, was relatively small, with significant variation noted across respondents. This could be due to respondents interpreting the question as referring to the planning team only, and not inclusive of the department as whole including treatment teams. This could also be attributed to staff shortages, which may increase the demand for technological assistance in managing time-consuming and attention-intensive tasks.[39]

This is the first study to elicit preferences for AI adoption in RT planning in Australia. It included radiation oncology professionals involved in RT planning including radiation therapists who are engaged in a variety of activities in RT planning and delivery process. The inclusion of a variety of background characteristics and information on attitudes and opinions related to AI adoption in RT planning allowed us to further investigate respondents' attitudes to adoption of AI in RT planning. Overall, the DCE provides important information to understand and plan for the adoption of AI in RT and the transformative potential of AI in streamlining processes, improving outcomes, and reducing costs. However, it should be noted that the DCE attributes may not reflect all aspects of the complex reality of experience of HCPs with AI in RT. There may be other relevant attributes not included in the choice tasks such as cost of AI systems (including implementation costs), impact on professional development and skills, as suggested by respondent feedback. Since no financial incentives were provided, recruitment depended solely on respondents' interest, making those with a strong interest in AI or strong opinions about it more likely to participate. This limitation is an inherent aspect of the study design, as participation cannot be enforced. However, the survey was distributed through multiple channels to ensure broad coverage of relevant HCPs.

Future research should investigate the reasons behind differences in preferences. Preferences are likely influenced by respondents' experiences and other individual characteristics and external factors, which were not explicitly addressed in this study. Although information about the respondents' professional experience was collected, the sample size was too small to allow for subgroup analysis of class-specific respondent characteristics.

Conclusions

This study provides important information about HCPs' priorities for AI in treatment planning. The results showed they preferred AI systems that offer the largest time saving, and that provide explanations of the AI reasoning (both in-depth and basic). They also favoured systems that provide improved contouring precision compared with manual systems. Respondents emphasised the importance of AI systems being cost-effective, while also recognising AI's impact on professional roles, responsibilities, and service delivery. The findings from this study can be used to inform future research on economic evaluations and management perspectives of AI-driven technologies in RT.

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Conflict of Interest

The authors declare no conflict of interest. The authors have no relevant financial or non-financial interests to disclose.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Ethical Approval Statement

This study was approved by the University of Technology Health Research Ethics Committee, ETH21-6090, 10 November 2023.

Informed consent statement

Informed consent was obtained from all subjects involved in the study.

References

1. Australian Institute of Health and Welfare. Cancer in Australia 2021. Australian Government Publishing Service, Canberra, 2021. Available from: https://www.aihw.gov.au/reports/cancer/cancer-in-australia-2021/summary (accessed 5 December 2024).
2. Australian Institute of Health and Welfare. Cancer. Australia's Health Topic. Australian Government Publishing, Canberra, 2024. Available from: https://www.aihw.gov.au/reports/australias-health/cancer (accessed 5 December 2024).
3. Australian Institute of Health and Welfare. Radiotherapy Overview. Australian Government Publishing, Canberra, 2024. Available from: https://www.aihw.gov.au/reports-data/health-welfare-services/radiotherapy/overview (accessed 5 December 2024).
4. Mun SK, Dieterich S (eds). Artificial intelligence. Radiation Oncology. World Scientific Publishing Company, Singapore, 2023; 372.
5. Santoro M, Strolin S, Paolani G, et al. Recent applications of artificial intelligence in radiotherapy: where we are and beyond. *Appl Sci* 2022; **12**: 3223.
6. Khalifa M, Albadawy M. AI in diagnostic imaging: Revolutionising accuracy and efficiency. *Comput Methods Programs Biomed Update* 2024; **1**: 100146.
7. Ge J, Li M, Delk MB, Lai JC. A Comparison of a large language model vs manual chart review for the extraction of data elements from the electronic health record. *Gastroenterology* 2024; **166**: 707–709.e3.
8. Lång K, Josefsson V, Larsson AM, et al. Artificial intelligence-supported screen reading versus standard double reading in the Mammography Screening with Artificial Intelligence trial (MASAI): a clinical safety analysis of a randomised, controlled, non-inferiority, single-blinded, screening accuracy study. *Lancet Oncol* 2023; **24**: 936–44.
9. Polymeri E, Johnsson ÅA, Enqvist O, et al. Artificial intelligence-based organ delineation for radiation treatment planning of prostate cancer on computed tomography. *Adv Radiat Oncol* 2024; **9**: 101383.
10. Marin AV. Artificial intelligence based auto-contouring solutions for use in radiotherapy treatment planning of head and neck cancer. *IPEM-Transl* 2023; **1**: 100018.
11. Sarria GR, Kugel F, Roehner F, et al. Artificial Intelligence–Based Autosegmentation: Advantages in Delineation, Absorbed Dose-Distribution, and Logistics. *Adv Radiat Oncol* 2023; **9**: 101394.
12. Topol EJ. High-performance medicine: the convergence of human and artificial intelligence. *Nat Med* 2019; **25**: 44–56.
13. Nazer LH, Zatarah R, Waldrip S, et al. Bias in artificial intelligence algorithms and recommendations for mitigation. *PLOS Digit Health* 2023; **2**: e0000278.
14. McCradden MD, Joshi S, Mazwi M, Anderson JA. Ethical limitations of algorithmic fairness solutions in health care machine learning. *Lancet Digit Health* 2020; **2**: e221–3.
15. Ahmed MI, Spooner B, Isherwood J, Lane M, Orrock E, Dennison A. A systematic review of the barriers to the implementation of artificial intelligence in healthcare. *Cureus* 2023; **15**: e46454.
16. Chew HSJ, Achananuparp P. Perceptions and Needs of Artificial Intelligence in Health Care to Increase Adoption: Scoping Review. *J Med Internet Res* 2022; **24**: e32939.
17. O'Shaughnessey J, Collins ML. Radiation therapist perceptions on how artificial intelligence may affect their role and practice. *J Med Radiat Sci* 2023; **70**(S2): 6–14.
18. Hallamaa J. Improving AI Systems Through Trade-Offs Between Values. *International Conference on Human-Computer Interactions* 2022 Jun 16 (pp. 329–333). Springer International Publishing.
19. Shinners L, Aggar C, Grace S, Smith S. Exploring healthcare professionals' understanding and experiences of artificial intelligence technology use in the delivery of healthcare: An integrative review. *Health Informatics J* 2020; **26**: 1225–36.
20. Batumalai V, Jameson MG, King O, et al. Cautiously optimistic: A survey of radiation oncology professionals' perceptions of automation in radiotherapy planning. *Tech Innov Patient Support Radiat Oncol* 2020; **16**: 58–64.
21. Brouwer CL, Dinkla AM, Vandewinckele L, et al. Machine learning applications in radiation oncology: Current use and needs to support clinical implementation. *Phys Imaging Radiat Oncol* 2020; **16**: 144–8.
22. Castagno S, Khalifa M. Perceptions of Artificial intelligence among healthcare staff: A Qualitative Survey Study. *Front Artif Intell* 2020; **3**: 578983.
23. Coakley S, Young R, Moore N, et al. Radiographers' knowledge, attitudes and expectations of artificial intelligence in medical imaging. *Radiography* 2022; **28**: 943–8.

24. Ryan M, Gerard K, Amaya-Amaya M (eds). Using discrete choice experiments to value health and health care. Springer, Dordrecht, 2008; 254 (The economics of non-market goods and resources).
25. Broberg T, Daniel AM, Persson L. Household preferences for load restrictions: Is there an effect of pro-environmental framing? *Energy Economics*; **97**: 202. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85101995985&doi=10.1016%2fj.eneco.2021.105188&partnerID=40&md5=fad92222918550e97495f5a369e593b4 (accessed 5 December 2024).
26. Cao Y, Cranfield J, Chen C, Widowski T. Heterogeneous informational and attitudinal impacts on consumer preferences for eggs from welfare enhanced cage systems. *Food Policy* 2021; **99**: 101979.
27. Godden E, Thornton L, Avramova Y, Dens N. High hopes for front-of-pack (FOP) nutrition labels? A conjoint analysis on the trade-offs between a FOP label, nutrition claims, brand and price for different consumer segments. *Appetite* 2023; **1**: 106356.
28. Hellali W, Korai B, Lambert R. Food from waste: The effect of information and attitude towards risk on consumers' willingness to pay. *Food Qual Prefer Vol 110* 2023. Available from: https://www.scopus.com/inward/record.uri?eid=2-s2.0-85166651149&doi=10.1016%2fj.foodqual.2023.104945&partnerID=40&md5=2bdfc3b893ce7fba5e919b5c545f4ec3.
29. Schatzmann T, Molloy J, Axhausen KW. Implementing web-based discrete choice experiments in transportation. *Transp Res Procedia* 2024; **1**: 586–95.
30. Bridges JFP, Bekkergrob EW, Hauber B, et al. A Roadmap for Increasing the Usefulness and Impact of Patient-Preference Studies in Decision Making in Health: A Good Practices Report of an ISPOR Task Force. *Value Health* 2023; **26**: 153–62.
31. Traets F, Sanchez DG, Vandebroek M. Generating Optimal Designs for Discrete Choice Experiments in R: The idefix Package. *J Stat Softw* 2020; **96**: 1–41.
32. RStudio Team. RStudio: Integrated Development for R. RStudio, PBC, Boston, MA [Internet]. PBC, Boston, MA. 2024 http://www.rstudio.com/.
33. Sarrias M, Daziano R. Multinomial logit models with continuous and discrete individual heterogeneity in *R* : The gmnl Package. *Journal of Statistical Software* 2017; **79** (2): 1–47.
34. Dziak JJ, Coffman DL, Lanza ST, Li R, Jermiin LS. Sensitivity and specificity of information criteria. *Brief Bioinform* 2020; **21**(2): 553–65.
35. Von Wedel P, Hagist C. Physician's preferences for and willingness-to-pay for artificial intelligence-based assistance tools: A discrete choice experiment among geman radiologists. *BMC Health Services Research* 2022; **22**: 398.
36. Thompson SC, Cheetham S, Baxi S. The enablers, barriers and preferences of accessing radiation therapy facilities in the rural developed world – a systematic review. *BMC Cancer* 2017; **17**: 794.
37. Hindocha S, Zucker K, Jena R, et al. Artificial Intelligence for Radiotherapy Auto-Contouring: Current Use, Perceptions of and Barriers to Implementation. *Clin Oncol* 2023; **35**: 219–26.
38. Bywall KS, Veldwijk J, Hansson MG, et al. Does being exposed to an educational tool influence patient preferences? The influence of an educational tool on patient preferences assessed by a discrete choice experiment. *Patient Educ Couns* 2021; **104**: 2577–85.
39. Debnath J. Radiology in the era of artificial intelligence (AI): Opportunities and challenges. *Med J Armed Forces India* 2023; **79**: 369–72.

Supporting Information

Additional supporting information may be found online in the Supporting Information section at the end of the article.

Appendix S1.
Appendix S2.