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Effective Adoption of Artificial Intelligence in Healthcare: A Multiple Case Study

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ABSTRACT

Adopting AI-based solutions is now widely regarded as an essential consideration in organisations' innovation strategies. For healthcare institutions, such solutions are an especially promising means to address societal and organisational challenges, including rising demand combined with shortages of qualified staff. The technology may enhance the efficiency of, for example, detecting diseases and planning treatments, which are time-consuming when executed manually. However, empirical research related to how AI can be effectively adopted in healthcare to harness these opportunities remains scarce. To address this gap, we conduct an exploratory multiple case study comprising 13 cases in the radiotherapy domain. Taking over an adoption theory perspective, we uncover that organisational, environmental, technological and individual factors are decisive for effective adoption of AI and contribute to the emergence of efficiency gains and standardisation. Our analysis reveals that organisational factors such as pursuing a dedicated innovation strategy within the radiotherapy department as well as a holistic AI implementation strategy are most crucial. In determining and relating the identified relevant factors, we contribute to adoption theory and AI-enabled value creation in healthcare. Further, we advise managers of healthcare institutions on how to effectively adopt AI to overcome challenges at organisational and societal levels.

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1. Introduction

The adoption of AI-based solutions is now widely considered a crucial component of organisational innovation strategies. This is because organisations applying the problem-solving affordances of AI to automate internal processes can potentially create value through gains in efficiency and/or enhanced products and services (Correia & Matos,

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2021). This is especially relevant for healthcare institutions as AI-based innovation strategies constitute a promising path to address prevalent societal challenges (Holloway et al., 2021). Health systems are challenged by ageing populations, lacking access to healthcare and resource shortages (Court et al., 2023; Zahlan et al., 2023). AI adoption seems a fruitful innovation strategy to tackle those challenges (Li et al., 2023).

The capacities of AI are expanding exponentially, with AI here referring to 'machine learning methods in which the computer automatically learns from data (and experience), identifying underlying patterns in complex systems, to perform predictions' (Korreman et al., 2021, p. 104). Applied to the healthcare context, AI can be used to identify, for example, patterns or abnormalities along the entire patient pathway and forecast patient risks for specific diseases or treatment success with the aim to leverage efficiencies and improve clinical outcomes.

One clinical field that especially benefits from the innovation strategy of effectively adoption AI is radiotherapy (Meyer et al., 2018). According to Sung et al. (2021), radiotherapy is moving increasingly towards personalised care, while the number of cancer cases globally is expected to increase from 19.3 million in 2020 to 28.4 million in 2040. Half of these patients will require radiotherapy. As 70% of the patients will be resident in low- and middle-income countries, less than half of them will have access to required treatments (Court et al., 2023; Korreman et al., 2021). To close this gap, 50,000 additional experts would be required along with tremendously enhanced workflow efficiencies (Atun et al., 2015; Court et al., 2023).

AI has the potential to create value by leveraging much-needed efficiencies and standardisation, particularly if effectively adopted within the organ-at-risk contouring (OARC) step (Cardenas et al., 2021; Cha et al., 2021; Duan et al., 2022; Roberts et al., 2023; Vandewinckele et al., 2020; Wang et al., 2023). Despite its potential, AI adoption in OARC remains limited due to limited data availability to train or test algorithms, concerns regarding accuracy and workflow integration, costs and uncertain return on investments (e.g. Cardenas et al., 2021; El Naqa & Murphy, 2015; Thompson et al., 2018; Van Dijk et al., 2020).

Given the clinical and societal relevance of AI adoption in OARC specifically, academics become increasingly active in researching facilitators and barriers to adoption as well as value creation. However, most studies are based on anecdotal evidence and single-case studies. Although initial empirical studies exist on value leveraged by AI in OARC and on clinical implementation of the technology, these studies are tied to very specific contexts with limited generalisability (Mugabe, 2021; Robert et al., 2021).

Given the importance of safe and effective adoption of AI in healthcare and OARC specifically and the scarcity of related empirical studies (Robert et al., 2021; Vandewinckele et al., 2020), we aim at exploring how health institutions can effectively adopt AI. The expected theoretical contributions of this study are twofold. First, we aim at contributing to research on effective AI adoption in healthcare. Specifically, we anticipate adding the value which can be leveraged by AI adoption justifying investments and factors contributing to such effective adoption. Second, we aim at extending theories on technology adoption to the healthcare context to understand how the factors driving effective adoption need to be configured in this sector.

Anticipated practical implications include a nuanced understanding of the value leveraged by adoption of AI in healthcare and factors contributing to more widespread effective adoption (Chua et al., 2021; Mugabe, 2021). The first can support healthcare professionals' decision-making related to investments in AI applications to justify costs, whereas the second raises awareness of crucial factors for effective adoption and thus can guide managers to adopt AI effectively.

2. Background

2.1. Theoretical background

To explore how healthcare institutions can effectively adopt AI we draw on adoption theory. We derive the definition for effective adoption from the concept of effective use and define effective adoption as adopting 'a system in a way that helps attain the goals for using the system' (Burton-Jones & Grange, 2013, p. 633). The decision for adoption depends on factors on the individual and organisational levels. At the individual level, Venkatesh et al. (2003) propose the unified theory of acceptance and use of technology (UTAUT). This theory comprises three decisive factors fostering the intention to use technology: performance expectancy, effort expectancy and social influence (Venkatesh et al., 2016). Related to the healthcare context, these determinants can help to understand how healthcare staff assess the usefulness of AI in their distinct environments. This allows us to gain insights into factors fostering and hindering the effective AI adoption in this sector.

At the organisational level, Tornatzky and Fleischer (1990) developed the technology – organisation – environment model (TOE Model). Technological factors include the resources required for the adoption of technology on an organisational level (Khemthong & Roberts, 2006), reliability, security and relative cost advantages. Organisational factors encompass firm scope and size, the centralisation and formalisation of an organisation and the availability and utilisation of internal resources (Pillai & Sivathanu, 2020). Lastly, the environmental perspective covers competition, governmental policies and regulations. In terms of healthcare, the TOE model adds a broader perspective to the UTAUT model and sheds light on the complexity of AI adoption. This involves not only compliance with laws and regulations but also, for example, available and trained clinical staff and mature technology ready for clinical use.

Related to our research objective, we deduct from adoption theory that factors on individual and organisational levels are crucial for effective AI adoption in healthcare institutions (Awa et al., 2017; Roppelt et al., 2023, 2024). Further, by focusing not just the decision to adopt but also the effective use of AI (Burton-Jones & Grange, 2013) we can uncover which configurations of the factors driving adoption result in effective AI adoption in OARC and thus create the anticipated value (Awa et al., 2017).

2.2. Related work

Our selective, conceptual literature review (cf. Cooper, 1988) revealed two streams of relevant literature: (1) empirical studies on the value leveraged through AI adoption in OARC, (2) studies on the clinical implementation of AI in OARC.

Most empirical research circles around the clinical evaluation of OARC algorithms and resulting time savings (e.g. Cardenas et al., 2021; Cha et al., 2021; Duan et al., 2022; Wang et al., 2023). Although Porter et al. (2016) call for evaluating the value of AI in radiation therapy by investigating the health outcome relative to the associated costs, only few studies move beyond the evaluation of quality of contours and time savings. In this vein, Duan et al. (2022) conducted a study evaluating the impact of automated OARC on the quality of the treatment plan (Duan et al., 2022). They found that the quality of the treatment plan after automatic contouring is clinically acceptable as it was comparable to the quality of the plan after manual contouring (Duan et al., 2022). Moreover, Mugabe (2021) found based on survey research that AI results in improved standards of care, fewer side effects and enhanced quality of life as well as improved efficiency and cost advantages. However, these studies are tied to very specific contexts such as New Zealand (Mugabe, 2021) and generalisability of the findings cannot be ensured. Consequently, the current state of literature lacks empirical, and generalisable studies regarding which value can be realised through adopting AI in OARC beyond direct time savings.

The only empirical studies – according to the authors' knowledge – outlining relevant factors for clinical implementation emphasise the need for educational concepts for clinical staff which also teach ethical considerations (Brouwer et al., 2020; Hindocha et al., 2023). Furhter, anecdotal evidence and literature reviews shed light on factors on technological, environmental, organisational and individual levels crucial for effective adoption (see Appendix A). Despite initial insights, these reviews lack empirical underpinnings and are again tied to specific contexts such as, e.g., France (Robert et al., 2021).

Despite the importance of safe and effective implementation and adoption of AI in OARC, empirical literature on clinical implementation and factors triggering effective adoption remains scarce (Robert et al., 2021; Vandewinckele et al., 2020). Literature lacks a theoretically grounded model incorporating both potential value (beyond time savings) which can be leveraged through AI adoption in OARC and triggering factors (cf. Walk et al., 2023; Wiljer & Hakim, 2019). Closing this gap has the potential to foster further adoption and thus contributing to offer more access to RT care in future, tackling societal challenges such as shortage of qualified staff while seeing an increase in demand for RT (Chua et al., 2021; Mugabe, 2021). Taking this observation and prevalent calls from literature on providing shared experiences regarding clinical implementation (e.g. Robert et al., 2021) into consideration, we formulate our research question as follows:

RQ: How can health institutions effectively adopt AI in OARC?

3. Materials and methods

As knowledge on our research objective is not rich enough to provide a sound theoretical foundation, we conduct a multiple case study (Eisenhardt, 1989; Yin, 2014). We perceive this methodology as promising as it enables insights from several perspectives in complex phenomena of organisations, such as the AI adoption in healthcare institutions (Eisenhardt, 1989).

3.1. Data collection

We aimed at constructing a representative sample by including a diverse set of health institutions covering emerging and developed markets, diverse geographical regions (United States, Europe, Asia and Australia) and different types of health institutions (public hospitals and private clinics).

Given this goal, we combined purposeful with convenience sampling complemented with snowballing and theoretical sampling to discover relevant cases (Iacobucci & Churchill, 2010). Thus, we first reached out to contacts within our networks such as representatives of hospitals (e.g. physicists and radiation oncologists responsible for the clinical implementation/adoption of AI) and AI vendors with experience of adopting or consulting on the adoption and implementation of AI in OARC. Second, we asked at the conclusion of each interview our respondents for additional potential interview partners able to offer either a new perspective on a given case or access to further cases until we reached theoretical saturation.

In this vein, we reached representativeness of our iteratively identified constructs, consistent with theoretical sampling (Charmaz, 2014; Glaser & Strauss, 1967). In total, we identified 13 cases as detailed in Table 1.

To foster multiple perspectives on each case and strengthen the grounding of our findings, we triangulated our data collection (Eisenhardt, 1989).

Interviews. After piloting our interview protocol with radiotherapy experts and having iteratively adjusted our questionnaire, we conducted 30 semi-structured in-depth interviews (lasting an average of 45 min each) in November–December 2023. All interviews were recorded and transcribed verbatim for subsequent analysis. The questionnaire can be found in Appendix B.

Supplemental materials. Finally, we obtained supplemental materials from our interviewees and their organisations' homepages. These include MS PowerPoint presentations, whitepapers and clinical studies, as well as other contents from their websites. Altogether we gathered 297 pages, which were analysed as part of the respective cases.

3.2. Data analysis

Our data analysis followed a two-step approach of within-case and cross-case analyses (Eisenhardt, 1989). For our within-case analyses, we first developed detailed case-study descriptions (Eisenhardt, 1989) of each organisation's innovation strategy and adoption of AI. These write-ups contain descriptions of the value leveraged per case post-AI adoption as well as respective triggering factors. To analyse the cases, extract relevant information and identify patterns for each case, we pursued a three-step coding approach by using the qualitative data analysis software MAXQDA (Strauss & Corbin, 1990). The first case was coded by two researchers independently, and variations were aligned (Boyatzis, 1998). The remaining cases were coded by one researcher and reviewed by the second.

First, we extracted conceptual insights through open coding. Then, similar codes were combined to create a single common terminology using the smart coding functionality of MAXQDA. This thorough procedure allowed the identification of first-order categories mimicking the perspectives of the individual cases.

Table 1. Sample characteristics.

Case	Regional cluster	Hospital type	Patients (year)	Supplemental material	Interviewee	Interview date	Duration (min)
ANZ1	Australia/ New Zealand	Public	<10,000	Data privacy & IT documentation, product related documentation, relevant emails	Implementation consultant 12	Nov 23	47
					Implementation consultant 16	Nov 23	49
					Physicist 4	Nov 23	38
ANZ2	Australia/ New Zealand	Private	<20,000	Implementation guide, training materials, nomenclatures	Physicist 3	Nov 23	52
CE1	Central Europe	Private	<10,000	Whitepaper on customer benefits	Implementation consultant 13	Nov 23	50
CE2	Central Europe	Private	<10,000	LinkedIn Post, manager magazine article	Implementation consultant 6	Nov 23	33
					Technologist 2	Nov 23	40
CE3	Central Europe	Public	<10,000	Publicly available innovation strategy; clinical study on workflow enabled by OARC	Implementation consultant 14	Nov 23	38
CE4	Central Europe	Public	<20,000	Publicly available innovation strategy	Implementation consultant 9	Nov 23	51
					Implementation consultant 10	Nov 23	47
EE1	Eastern Europe	Private	<10,000	Corporate marketing video on value generated through OARC	Implementation consultant 3	Nov 23	42
					Physician 3	Dec 23	50
					Physicist 2		
EE2	Eastern Europe	Private	>20,000	n. a.	Physician 1	Nov 23	41
					Implementation consultant 5	Nov 23	52
					Implementation consultant 8	Nov 23	48
ASN1	Asia	Private	>20,000	Scientific publication on evaluation of OARC solutions across multiple centres	Physicist 1	Nov 23	42
					Physician 2	Nov 23	29
ASN2	Asia	Private	<10,000	PowerPoint slide on implementation and value creation	Implementation consultant 11	Nov 23	42
					Implementation consultant 13	Nov 23	53
US1	United States	Private	<20,000	Vendor-owned MS PowerPoint presentation on implementation of OARC	Technologist 1	Nov 23	44
					Implementation consultant 2	Nov 23	40
					Implementation consultant 4	Nov 23	50
US2	United States	Private	<10,000	Presentation on quality of individual contours and time savings	Dosimetrist 1	Nov 23	39
					Dosimetrist 2	Nov 23	52
US3	United States	Public	<10,000	n. a.	Dosimetrist 3	Nov 23	54
Experts	United States	Private	<20,000	n. a.	Implementation consultant 15	Nov 23	55
	Central Europe	Public	<20,000	n. a.	Implementation consultant 1	Nov 23	46
	Central Europe	Private	<10,000	n. a.	Implementation Consultant 7	Nov 23	35
	Central Europe	Public	<10,000	n. a.	Implementation Consultant 18	Nov 23	38

Note: patient numbers were clustered to preserve anonymity of cases. Source: authors' own work.

Second, we applied axial coding to analyse how the first-order categories relate to each other and identify their overarching concepts. For instance, we theorised codes such as 'Increase in patients due to screening programs', 'increasing occurrence of cancer', 'Increasing workload for patients due to increased complexity of cancer cases' as the second-order-theme 'Increase in demand'.

Third, we conducted selective coding and subsumed the overarching concepts comprising value to aggregate dimensions. For example, we clustered 'Reduced time to treatment', 'Reduced levels of stress', 'Enhanced quality of care', 'Enhanced job attractivity', 'Overcome staffing challenges' and 'Financial impact' as 'Efficiency'. The overarching concepts subsuming factors triggering effective adoption were allocated to pre-defined codes identified from adoption theory. Thus, we labelled them as 'organisational', 'technological', 'environmental' and 'individual' factors (O'Reilly et al., 2012). For instance, environmental factors encompass 'Scarcity of staff', 'Increase in demand' and 'Competition'. The final coding scheme can be found in Appendix C.

After having identified the value leveraged as well as triggering factors per case, we compared, first, the value created across the different cases, and second, the factors which were crucial for effective adoption to explain variations in the levels of value observed. Finally, we judged the degree ('low', 'medium', 'high') to which each value pillar was present in the individual cases and the level of effective adoption per case. Then, we analysed which factors contributed to which extend ('low', 'medium', 'high') to the cases' effective adoption process. The allocation of the labels 'low', 'medium' and 'high' was again performed by one researcher and reviewed by the second. To confirm the plausibility of our findings, we contacted two selected interviewees and organised a panel with 12 experienced scholars in our field to share and further refine the presentation and framing of our findings (Pratt, 2008; Tracy, 2010).

4. Results

Our resulting findings on how healthcare institutions can effectively adopt AI, specifically in OARC, are presented and discussed against prior research in a two-step approach. First, we shed light on the explored levels of value leveraged through AI adoption in OARC across our cases (4.1). Second, we outline the identified factors explaining variation in the value these organisations had attained from adopting AI and derive respective propositions (4.2).

4.1. *Value leveraged through AI adoption in OARC*

Our findings confirm anecdotal evidence and recent reviews that efficiency and standardisation constitute the predominant outcomes of adopting AI in OARC (cf. Cobanaj et al., 2024; Huynh et al., 2020; Robert et al., 2021; Vandewinckele et al., 2020). Although the level of effective adoption/value creation through AI differs among the cases, none reported the emergence of negative consequences or value. Specifically, some of our interviewees outlined that they do not perceive a risk for harmful forms of practice through AI in OARC as the AI has the potential to leverage efficiencies and standardisation and transform how radiation therapy is done today. In the OARC domain, they only

Table 2. Level of effective adoption by case.

	Level of generated efficiency						Level of generated standardisation		
Case	EP1	EP2	EP3	ES1	EC1	EC2	SS1	SS2	Level of effective adoption
ANZ1	Low	Low	Low	High	High	Low	Medium	Medium	Medium
ANZ2	High	Medium	High	High	High	High	High	High	High
CE1	High	High	High	High	Medium	High	High	Low	High
CE2	Low	Medium	Medium	Medium	Low	Medium	Medium	Low	Medium
CE3	High	High	High	Medium	Low	High	High	Medium	High
CE4*	Low	Medium	Low	High	Low	Low	Medium	Medium	Medium
EE1	High	High	High	High	High	High	High	Low	High
EE2*	Low	Medium	Low	High	Low	Low	Low	Medium	Low
ASN1	Low	Low	Low	High	Low	Low	Low	High	Low
ASN2	Medium	High	High	High	High	High	Medium	Low	Medium
US1	High	High	Low	Medium	High	Medium	High	High	Medium
US2	Medium	Medium	Low	High	Medium	Low	Medium	High	Medium
US3	Medium	Medium	Medium	High	High	Low	Medium	Low	Medium

Key: ANZ: Australia New Zealand; CE: Central Europe; EE: Eastern Europe; ASN: Asia, US: United States; EP1: Reduced time to treatment; EP2: Reduced levels of stress; EP3: Enhanced quality of care; ES1: Enhanced job attractiveness; EC1: Overcome staffing challenges; EC2: Financial impact; SS1: Enhanced confidence in treatment plans; SS2: Facilitation of cross-centre collaborations. All level-assessments constitute subjective assessments discussed by the authors and aligned: * newly integrated AI in their processes; higher levels of value related to reduced time to treatment, enhanced quality of care as well as higher overall value ratings are expected in a second step. Source: authors' own work.

perceive the risk of receiving less value than expected. The levels of value generated per case and value pillar are summarised in Table 2 and detailed below.

4.1.1. Efficiency

Our data provide evidence that realised efficiency gains through AI adoption translate in value for the OARC staff, patients and the RT clinic. Related to staff, the use of AI was reported to be especially beneficial in reducing the resources needed for the time-consuming and repetitive step of contouring, providing time to focus on tasks requiring greater expertise, and thus enhancing the general attractivity of the job. This positive perception was evinced by multiple respondents across all cases who oversee OARC:

> [In the past] we often contoured late at night – after nine p.m. if a patient needed treatment urgently. Now with AI it takes us around five minutes and we save hours. (CE2, Technologist 2)

Related to patients, our respondents reported that increased efficiencies led in their cases to reduced levels of patient stress, reduced time to treatment and enhanced quality of care. The more face-to-face time with patients enables staff to address not only the psychological stress but also the physiological stress by, for example, managing side effects. Our informants also emphasised that AI was also essential to reduce the number of visits (and associated stress through travelling) required by patients by enabling '*single-session treatment*' (ANZ2, Physicist 3).

The cases reaching high levels of effective adoption (ANZ2, CE1, CE3, EE1) also report significant time-to-treatment reductions and an enhanced quality of care as exemplary remembered by one of our interview partners:

> Previously we only contoured the ribs that were close to the target. Now with AI we can contour all [the patient's] ribs and see in the simulation the amount of dose which gets radiated to other organs as well. That's useful information to better plan subsequent treatments in case the patient relapses. We didn't have this information before. (EE1, Physician 3)

The enhanced quality of care is also reflected in the more personalised workflows, such as online adaptive workflows, facilitated/enabled by effective adoption of AI in OARC.

Finally, the clinics benefits leveraged by the efficiency gains are twofold. First, clinics market their more attractive and innovative work environment to attract scarce staff and overcome workforce shortages. Our interviewees report that the opportunity to focus less on the repetitive task of contouring and more on, e.g. complex cases positively contributes to attracting staff. Second, our interviewees of the cases with high-level of effective adoption outlined that efficiency gains help clinics to leverage financial impact through cost savings or the ability to excel a comprehensive growth strategy as exemplary outlined below:

> More patients (. . .) lead to more money which they can then again invest in new technology such as a new Halcyon. More money thus means more efficiency, more patients and of course also financial impact. (CE1, implementation consultant 14)

Other interview partners, however, recalled that their organisations do not capitalise on the efficiency gains as illustrated exemplary below:

> Our finance team did not like it, as the AI costs more than hiring experts to contour. In our country, staff is cheaper than the AI. (ASN1, physician 2)

4.1.2. Standardisation

Apart from efficiency gains, our sites also reported value through the enhanced level of standardisation enabled by AI adoption. The application of unified contouring guidelines as well as templates harmonising colours of organs and naming conventions both yield higher confidence in treatment plans and facilitate cross-centre collaborations.

Higher confidence in treatment plans, stems from less error prone treatment plans. By reducing variability and unifying colours and names of contours '*errors can be detected way faster. And it is also obvious if certain colors are missing*' (CE2, technologist 2).

Cross-centre collaborations are supported by the uniformed nomenclature through AI. This harmonisation facilitates the exchange of staff among centres in hospital networks and cross-centre research, as especially emphasised by, for example, EE2 and ANZ2.

4.2. How health institutions adopt AI in OARC effectively

Although all our cases report value through leveraged efficiencies and standardisation by adopting AI in OARC, Table 2 shows that the level of effective adoption varies among the cases. Our analysis indicates that four organisations (ANZ2, CE1, CE3 and EE1) have effectively adopted AI in OARC and extracted comparatively higher levels of value for relevant stakeholders. In turn, the nine remaining cases extract relatively low-to-medium levels of value.

Our study reveals that organisational, environmental, technological and individual factors are decisive for effective AI adoption, in line with propositions from adoption theory (Tornatzky & Fleischer, 1990; Venkatesh et al., 2016). Table 3 provides an overview of the variation in these factors and their respective pillars across the cases. Negligible differences in technological and individual factors were identified across the cases. Instead, the decisive differences were found in the organisational factors. Thus, we will

Table 3. Factors fostering effective adoption of AI in OARC.

		Organisational factors				Environmental factors		Technological factors		Individual factors	
Case	Level of effective adoption	OF1	OF2	OF3	OF4	EF1	EF2	TF1	TF2	IF1	IF2
ANZ1	Medium	Medium	Single	RTT	Holistic	High	Medium	High	High	High	Physicist
ANZ2	High	High	Multi	RTT	Holistic	High	High	High	High	High	Physicist
CE1	High	High	Single	Physicist	Holistic	Medium	High	High	High	High	Physicist
CE2	Medium	Low	Single	RTT	Acc-rel.	Medium	Medium	High	High	High	Physician
CE3	High	High	Multi	RTT	Holistic	Medium	High	High	High	High	Physicist
CE4	Medium*	Medium*	Single	Physicist	Holistic	Medium	High	Medium	Medium	High	Physicist
EE1	High	High	Single	Physician	Acc-rel.	High	High	High	High	High	Physicist
EE2	Low*	Low	Single	Physician	Acc-rel.	High	High	High	Medium	High	Physician
ASN1	Low	Low	Multi	Physicist	Holistic	Low	Low	High	High	High	Physician
ASN2	Medium	Medium	Single	Physicist	Holistic	Low	Medium	High	High	High	Physicist
US1	Medium	Medium	Multi	Dosimetrist	Holistic	Low	High	High	High	High	Physicist
US2	Medium	Medium	Multi	Dosimetrist	Holistic	Low	Low	High	High	High	Physicist
US3	Medium	Medium	Single	Dosimetrist	Acc-rel.	Low	Low	High	Medium	High	Dosimetrist

Key:OF1: Scope of innovation strategy; OF2: set-up of clinic; OF3: OARC responsibility; OF4: Implementation strategy; EF1: Scarcity of staff; EF2: Increase in demand; TF1: Technological maturity; FT2: Workflow integration; IF1: Mindset; IF2: Background, *: newly integrated AI in their process ➔ higher overall value ratings are expected in a second step and also extension of scope of innovation strategy expected; Single: single-site hospital; multi: multi-site hospital, RTT: Radiation therapy technologist; Acc-rel.: accuracy-related. Source: authors' own work.

the organisational factors most detailed, before we also shed light on the other factors fostering effective AI adoption.

4.2.1. Organisational factors

Organisational factors include scope of innovation and implementation strategies, the specific set-up of each clinic and whom responsibilities for conducting OARC were assigned.

Scope of innovation strategy refers to the decision whether a clinic implements AI-based OARC as part of a holistic innovation strategy to the RT department or whether OARC staff implements the solution solely in the OARC step to, e.g. realise efficiencies during OARC without optimising related processes. The centres reaching high levels of value creation/effective adoption (ANZ2, CE1, CE3, EE1) not only implemented AI in the OARC step but pursued an innovation strategy on RT department level as outlined by one exemplary clinician:

> We had to innovate our entire center. We grew over the last years from 13 people to a 100 and from 500 square meters to 3,000. To facilitate efficiencies, we implemented AI and also set up a new treatment machine to cope with the increasing number of patients. (EE1, Physician 3)

By contrast, the centres attaining medium-to-low levels of value through AI had taken a less holistic approach, either by innovating solely within the OARC step (e.g. US3, ASN1) or postponing the planned adaptation of related workflows as a separate step (e.g. CE4). CE4, for example, plan to enable adaptive workflows in future which will then allow them to gain high levels of value. However, to-date, they implement AI exclusively in the OARC step until technological maturity allows implementation of AI in their desired online adaptive/innovative workflows.

Generating efficiencies beyond the OARC step are according to our insights only feasible if related processes are adapted accordingly. If a clinic exclusively innovates the OARC step but does not consider dependencies to, for example, physicians or planning/treatment machine capacities, anticipated efficiencies such as faster time-to-treatment or financial gains cannot be realised (e.g. ASN1, US3). Thus, having an innovation strategy encompassing the entire RT department in place is essential to leverage high levels of value through AI in OARC.

Further, our findings emphasise the importance of excelling a subsequent structured innovation implementation approach. Our analysis outlines that centre which implemented AI in OARC in a structured way (e.g. ANZ2, CE1, CE3) leveraged higher levels of value compared to others. Structured innovation implementation includes according to our interview partners management support, definition of an implementation leaders (in most cases the physicist), structured assessment of the quality of contours and guidance on how workflows need to change, education of users, step-wise roll outs and sustainable adaptation of processes and workflows to not only ensure the generation of efficiencies but also the match of, for example, the training population with the target population. Exemplary, a physicist describes below how they implemented the innovation of AI in OARC:

> We first wrote work instructions explaining where the AI fails, when to adjust which contours, and so on. These instructions detail which buttons to press and when, how we adapt our

> workflows to create efficiencies, which scripting checks are required, et cetera. The biggest risk for us is that people start trusting in AI too much – thus we also outline which contours need to be drawn manually. (ANZ2, Physicist 3)

For single-site clinics, our analysis reveals that also a 'plug-and-play' approach can also result in high-levels of effective adoption (e.g. EE1). Due to the small size of the clinic and strong established ties among the staff members, new processes were identified and implemented without a structured assessment:

> We did not follow a strategic approach to implement AI. We analyzed which structures are needed by trial and error and then adopted templates, started auto routing of contours to treatment planning system and now the doctors can use it (EE1, physician 3).

Although this unstructured approach worked for this single-site (EE1), it seems to not work for multi-site clinics or academic public hospitals who only manage to reach medium/low level of value through AI adoption (CE2, EE2, US3). Thus, the set-up of the site (single site vs. multiple sites, complexity) is crucial regarding which level of implementation efforts are required.

Finally, also the role responsible for OARC is decisive, especially for the generation of financial impact. In clinics in which the technologists or students (e.g. ANZ1, CE2) oversee doing OARC, less financial impact was leveraged than at sites where the oncologists or physicists (e.g. EE1, EE2, ASN1) hold this responsibility, due to differences in salaries.

Thus, our insights trigger the following proposition:

Proposition 1: Organisations with organisational factors including comprehensive innovation and implementation strategies as well as relatively expensive OARC resources are positively associated with effective adoption/high levels of value creation through AI in OARC.

4.2.2. Environmental factors

Our insights reveal that the presented organisational factors are shaped by environmental factors. Environmental factors include the pressure of staff shortages and a rising demand for radiation therapy treatments (cf. Atun et al., 2015; Farina et al., 2022; Korreman et al., 2021). Our interview partners report that staff shortages include both a lack of qualified staff in general (CE1, CE2, CE3, CE4) and/or specifically a lack of staff in rural areas and emerging markets (EE1, EE2, ANZ1, ANZ2) as exemplary outlined by one physician:

> We see a yearly number of around 3,000 patients requiring radiosurgery in our country. This treatment is the only chance some patients have [to recovery]. That's why we'd like to enable it for everyone in need. We've already employed all good staff and there are no more staff in our country, so we need to find alternatives to generate efficiencies. (EE1, Physician 3)

Despite these variations in attained benefits, most of our interviewees acknowledged that AI constitutes a highly promising technology to overcome staffing challenges. In ANZ, for example, a clinic faced challenges to recruit staff and decided to use the budget intended for one headcount to acquire AI. We found that those organisations whose representatives most strongly emphasised the challenge of meeting the demands of an increasing number of patients were also most likely to have proactively and strategically introduced technological innovations in their radiotherapy departments and OARC processes with a view to creating value through capitalising on the use of AI.

Contrariwise, environmental factors like staff shortages appeared less salient a concern for interviewees from some centres, especially those from organisations that had also not invested significantly in organisational factors (e.g. ASN1, US3). Thus, we conclude that a stronger concern with and/or exposure to environmental factors can in turn trigger organisational factors that lead to the implementation of more holistic AI-based innovation strategies better suited for optimising efficiencies while maintaining a high standard of care.

Related to rising demand for radiation therapy resources, our interview partners report that the increasing availability and accessibility of screening programmes contributes to more patients with earlier stages of cancer which are eligible for radiation therapy treatment. At the same time, they see an increase in the number of cancer cases globally and an increasing workload as especially the number of complex cancer cases increases. Our analysis reveals that cases being especially challenged by rising demand for radiation therapy resources (e.g. ANZ2, CE1, CE3, EE1) tend to engage in more comprehensive innovation and implementation strategies, due to the strong need compared to others (e.g. US2, US3, ASN1).

Based on this data, we phrase the second proposition:

Proposition 2: Organisations facing high levels of environmental factors (staff shortages, rising demand of patients) will implement greater levels of organisational factors (e.g. comprehensive innovation and implementation strategies).

4.2.3. Technological factors

Although organisational and thus also environmental factors are according to our insights most decisive, also technological factors seem to influence effective AI adoption. Technological factors include technological maturity and the interoperability opportunities to allow a smooth integration in existing workflows. To assess technological maturity, our interviewees reported that they examine the physical performance of AI-based solutions. Moving beyond insights from prior research which show that clinicians evaluate clinical accuracy of contours (e.g. Cardenas et al., 2021; Wang et al., 2023), our insights further reveal that they also test '*if it's a safe and reproducible system, [clinicians] they really need to understand how the structures are in relation to each other to be able to perform the treatment planning*' (CE4, Implementation Consultant 10).

The AI's ability to be integrated seamlessly in existing workflows seems especially relevant for centres that do not innovate their RT department holistically and aim at benefiting from AI solely in the OARC step (ASN1, EE2, ASN2, US1, US2, US3).

Consequently, we formulate our third proposition as follows:

Proposition 3: Technological factors including high levels of technological maturity and workflow integration are positively associated with effective adoption of AI in OARC.

4.2.4. Individual factors

Finally, individual factors crucial for effective adoption comprise according to our insights individual's mindset and their backgrounds. Throughout our cases, the implementation

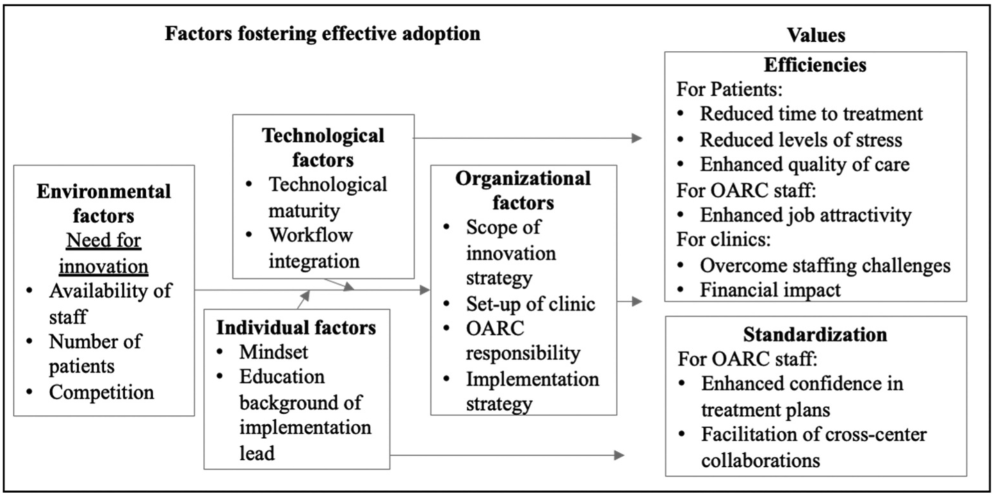

Figure 1. AI in organ-at-risk contouring: a framework on effective adoption.

leads held entrepreneurial mindsets, meaning they were open to new technologies, curious about innovating existing processes and trusting the technology, vendor and people involved. In all cases achieving medium-to-high level of effective adoption, the lead physicist led the implementation project due to the expertise in evaluating technological innovation and driving change across the clinic, as also recommended in prior research and literature (cf., Huynh et al., 2020; Schneider et al., 2022).

Taking our insights and literature into consideration, we derive the following fourth proposition:

Proposition 4: Individual factors including entrepreneurial mindsets and physics education are positively associated with the effective adoption/value creation of AI in OARC.

4.3. Summary

In conclusion, we found through our multiple case study that organisational factors are decisive for the effective AI adoption in OARC and thus, for capitalising on the leveraged efficiencies and standardisation. The level to which a healthcare institution engages in organisational factors seems according to our data dependent on the magnitude of environmental factors which affect the clinic. We infer from our analysis that technological and individual factors also directly influence effective adoption. Additionally, technological and individual factors seem to influence the relationship from environmental factors to organisational factors. Given technological mature solutions and individuals holding an entrepreneurial mindset, health institutions seem to rather innovate their RT department. Consequently, we phrase our fifth and sixth proposition as follows:

Proposition 5: Technological factors including high levels of technological maturity and workflow integration positively moderate the effect of environmental factors on organisational factors.

Proposition 6: Individual factors including entrepreneurial mindsets and physics education positively moderate the effect of environmental factors on organisational factors.

To summarise our findings, we introduce the '*AI in organ-at-risk contouring: A framework on effective adoption*' model, as depicted in Figure 1.

5. Discussion

5.1. Contributions to the literature on AI adoption in healthcare

Our study set out with the aim of exploring how healthcare institutions can adopt AI-based solutions effectively. Although prior research has examined the value leveraged through AI adoption in OARC and strategies to implement AI in OARC clinically, these studies were tied to specific endpoints (time savings, evaluation of quality of organs, impact on treatment plan) (e.g. Cardenas et al., 2021) or contexts (e.g. Mugabe, 2021). Thus, our multiple-case study – encompassing a diverse data set – adds to prior research by identifying how gains in efficiency and standardisation translate into specific value for patients, OARC staff and radiotherapy clinics across treatment sites, hospital types and geographical regions.

Moreover, we shed light on the factors explaining the variations of our cases regarding their level of effective adoption. Prior empirical research outlined the importance of organisational factors by emphasising the need for educational concepts for clinical staff to teach, for example, ethical considerations (Brouwer et al., 2020; Hindocha et al., 2023). Moving beyond prior research, we empirically uncovered the decisive role of organisational factors to reach effective AI adoption and their dependencies to environmental, technological and individual factors. Further, we add an empirically derived nuanced understanding of the pillars of each factor and propose respective propositions. For organisational factors, for example, we reveal the crucial role of pursuing comprehensive innovation and implementation strategies to reach high level of value through AI adoption. The importance of a structured implementation approach is mimicked by anecdotal evidence suggesting that health institutions perform commissioning of AI software including documentation of limitations to guide users, adjustment of processes and development of educational resources (Huynh et al., 2020; Rong et al., 2024; Vandewinckele et al., 2020).

Related to theory on effective adoption, our findings echo prior recommendations to complement the TOE model, with another model considering factors on individual level (cf. Awa et al., 2017). While the TOE and UTAUT model comprise factors on technological, organisational and environmental levels as well as individual level, we contextualise the factors specifically for the OARC domain and outline their interdependencies to achieve effective adoption of AI in OARC and highlight the decisive role of organisational factors. We explored that these organisational factors become triggered by environmental factors. Our qualitative data indicates that this effect is influenced by individual and technological factors, awaiting quantitative validation.

5.2. Limitations and avenues for further research

Besides the contributions, our study is subject to limitations opening opportunities for future research. First, in the scope of this study, we considered each realised and reported value as equally important and did not weigh them differently to identify the overall level of effective adoption per case. However, we interestingly found as a side product that high-level of effective adoption seems to be specifically associated with financial impacts, enhanced patient outcomes and reduced time to treatment. Cases of low-to-medium level of effective adoption have not realised these values. This observation suggests a dependency among the identified values. To further understand this dependency and guide managers to realise anticipated values strategically, we call for future research on examining how the different value pillars relate to and depend on each other through further research. We recommend mixed method studies to first explore the dependencies and then text them empirically.

Second, although we explored the factors (and their pillars) crucial for effective adoption, we could not quantify the impact on leveraging anticipated values or reaching effective adoption. Especially for providing personalised advice to health institutions' managers dependent on the hospital's characteristics, history and ambitions, it may be desirable to understand which configuration of factors translates to the generation of which set of values. Thus, we call for experimental research to understand this relationship and provide personal guidance to health institutions dependent on their specific case.

Third, we are confident that most of our findings are transferable to other clinical fields, especially related to technological and individual factors. However, radiotherapy is comparably complex requiring highly specialised staff (e.g. Korreman et al., 2021; Meyer et al., 2018), whereas other clinical fields may be less complex resulting in potentially different environmental factors. As environmental factors may differ across different contexts, also the impacted crucial organisational factors may be different. Thus, we call for future research investigating further contexts to explore whether the identified findings are generalisable.

Finally, our research builds on a multiple case study within the OARC domain and awaits quantitative validation of the derived propositions. Consequently, we call for research testing the proposed relationships quantitatively by, for example, applying structural equation modelling. This analysis may be complemented by an analysis of variance, exploring differences among groups such as hospital types or geographical regions in line with propositions from contingency theory (e.g. Aragón-Correa & Sharma, 2003; Wade & Hulland, 2004). Resulting evidence can support the development of more precise guidance for practitioners on how to adopt AI in healthcare institutions effectively.

5.3. Practical implications

Our findings have implications for healthcare institutions and AI vendors alike. For healthcare institutions, our insights into the value that can be created from generating efficiencies and standardisation through adopting AI – including reduced time to treatment for patients, enhanced job attractiveness for staff and financial opportunities for the clinic – may support healthcare institutions' decision-making processes on whether to invest in AI-based solutions. Having this information, health institutions can compute the expected return on investment to take an informed decision on whether adopting AI will pay off in their institution.

Additionally, we contextualised the factors crucial for effective AI adoption in healthcare institutions based on the OARC example and thus guide managers to adopt AI effectively. Our findings help managers understand the need for a comprehensive innovation and implementation strategy to effectively adopt AI and realise anticipated value. Such an innovative strategy needs to not only focus on the individual OARC step but also encompass all related functions and process steps, addressing bottlenecks in the workflow, so that the potential of AI can flourish. Following a systematic implementation strategy involves the structured evaluation of the AI results, and a change management strategy including, e.g., guidelines on how to use AI, what are the limitations of AI, when to not use AI, when/how to adapt AI's output, etc.

Finally, based on our insights, AI providers shall not only focus on developing technologically mature solutions which have been validated internally and externally but also to proactively guide healthcare institutions on how to set up AI for optimising workflows and harnessing value for affected stakeholders. Fuelled by their experience in AI implementation and adoption projects, vendors are in a promising role to guide health institutions to implement innovation and AI implementation strategies effectively so that the anticipated value can be leveraged.

Disclosure statement

The first author is employed at a multi-national corporation also selling organ-at-risk contouring solutions. The other authors report no competing interest to declare.

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Appendices

Appendix A

Table A1. Anecdotal evidence and insights from literature reviews on factors driving adoption.

Factors driving adoption	Findings from selective, conceptual literature review	References
Technological factors	Technological maturity Establish credibility in algorithms by e.g. adding confidence scores	Li et al. (2023)
Organizational factors	Commissioning of AI software: ● quality assessment of algorithms' output per clinical site ● clear documentation of limitations and inaccurate performance to guide users ● adjustment of processes and workflows to ensure humans review AI outputs (and do not fully rely on AI) ● Development of educational resources Redefinition of existing roles for staff responsible for OARC for physicist who is recommended to oversee the AI adoption/implementation due to skills	Huynh et al. (2020) Rong et al. (2024) Vandewinckele et al. (2020)
Environmental factors	Clarification of liability questions Standardised reporting of AI studies to facilitate AI adoption in OARC	Huynh et al. (2020) Parkinson et al. (2021)
Individual factors	Familiarity with AI of staff Openness to adopt and implement AI	Parkinson et al., (2021)

authors' own work.

Appendix B

Interview guideline

Cursive passages are only for the interviewer and meant to be a thought -provoking impulse to navigate the interview
(German or English)

Table B1. Interview guideline.

Part 1: Introduction	• Brief introduction of researcher and interviewee (area of responsibility and position in company) • Objective: gain first-hand knowledge and explore how the adoption of AI in radiation therapy may create value for various stakeholders in a health institution's environment • Duration: approx. 45 min • Data privacy: all information will be treated anonymously. No obligation to answer to individual questions. The interviewee can be terminated at any point in time. Also, after the interview, possibility to exclude this interview's data if needed. The interview will be recorded to be transcribed; the audio will be deleted immediately after. • In particular, we are curious about your personal experiences and perspectives, and it would be great if you can think of a concrete example when answering our questions. • After having successfully completed our study, we are happy to share our insights with you.
Part 2: Definition of Artificial Intelligence	To ensure a joint understanding of the term: Could you please describe your understanding of "Artificial Intelligence"?
Part 3: Innovation strategy	Could you please describe your institution's short-, mid-, and long-term innovation strategy? • Which objectives do you aim at achieving in the mid- and long-term? • Why do you (your institution) aim at achieving these objectives? What drives your institution? • How do you plan to reach your objectives? • Does AI play a role in reaching your objectives? If yes, could you please describe the role of AI in your institution's innovation strategy? How does it contribute to reach your goals?

(*Continued*)

Table B1. (Continued).

Part 4: AI adoption	(a) *AI adoption in RT department* What kind of AI application have you heard of/tried in the field of radiation therapy? Which AI solutions have you adopted in your RT department? Why did you adopt these AI solutions? What drove your decision? (a) *Value leveraged by AI adoption in RT department/OARC* Which stakeholders are impacted (positively or negatively) by the adoption of AI in radiation therapy (OARC specifically)? *(Radiation therapist, physicist, dosimetrist, technologist, Oncologist, Radiologist, Quality manager, Finance department, Administration, Patient, community, Finance?)* What kind of value (positive and negative) got leveraged by the adoption of AI in your radiotherapy department? *(repeat question for each relevant stakeholder)* Is this value directly attributable to the adoption of AI in Oncology at your center or were there also other factors influencing/did other conditions contribute to the generation of this value? Looking in the mid- and long-term future – which additional value do you anticipate being leveraged? How long will these anticipated gains/losses last? Why? (*Positive and negative value*) Is this value directly attributable to the adoption of AI in Oncology at your center or were there also other factors influencing/did other conditions contribute to the generation of this value? (a) *Factors contributing to effective adoption/value creation through AI adoption in radiation therapy/OARC* How did you implement/adopt AI in your radiation therapy department/OARC department so that this value can be leveraged? Which factors along the implementation/adoption journey drove the effective adoption/value creation of AI in your RT department/OARC step? Which ones do you consider most important? Why? Which factors were crucial that you can now harvest value? *Hints (if needed)*: ● *Environmental factors* ● *Organisational factors* ● *Individual factors* ● *Technological factors*
Part 5: Open topics	We are approaching the end of the interview now. ● Are there any additional insights you would like to share with us on the discussed topic? ● Based on your expert opinion in the field of radiation therapy; can you recommend further promising interview partners such as key opinion leaders in this field (and cases) we should include in our sample? Could you please connect us accordingly?
Part 6: Closing	Before we close, we have demographical questions: ● How do you describe your role? ● How long are you already in your current position? What was your previous position about? ● How do you classify your health institution's type? (public clinic, private clinic) ● Can we reach out in case further questions come up? ● Can we reach out again to share and discuss our preliminary findings? ● Next steps: share findings once study completed Thank you very much for your time. That is highly appreciated.

authors' own work.

Appendix C

Table C1. Data structure on value created by AI adoption in OARC.

Aggregate dimensions	Second-order themes	First-order categories
Efficiency	*For patients* (EP)	
	EP1: Reduced time to treatment	• Reduce waiting time for patients to start treatment • Accelerate time to treatment for patients from remote areas
	EP2: Reduced levels of stress	• Less physical stress • Less emotional stress • Less stress due to reduced amount of required travelling
	EP3: Enhanced quality of care	• Contouring of additional organs • Facilitation of personalised workflows
	For OARC staff (ES)	
	ES1: Enhanced job attractiveness	• Focus on non-repetitive tasks such as scripting, research, complex cases, patients (e.g. managing side effects) • Reduced stress levels/risk of burnout
	For the clinic (EC)	
	EC1: Managing staffing challenges	• Enhanced ability to handle staff fluctuations • Enhanced ability to overcome staffing challenges (in rural areas) • Ability to attract staff
	EC2: Financial gains	• Growth of clinic • Reduction of external costs • Reduction of internal costs
Standardisation	*For OARC staff (SS)*	
	SS1: Enhanced confidence in treatment plans	• Less error-prone treatment plans • Facilitation of treatment planning
	SS2: Facilitation of cross-centre collaborations	• Facilitation of exchanging people among centres • Facilitation of cross-centre research studies

authors' own work.

Table C2. Coding scheme excerpt regarding factors triggering effective AI adoption in OARC.

Aggregate dimension	Second-order theme	First-order construct
Environmental Factors (EF)	EF1: Scarcity of staff	• Lack of qualified staff • Lack of staff in rural areas
	EF2: Increase in demand	• Increase in patients due to screening programs • Increasing workload due to increasing number of complex cases • Increasing cancer occurrence
Technological Factors (TF)	TF1: Technological maturity	• Clinical performance • Physical performance • Mature technology
	TF2: Workflow integration	• Seamless integration in hospital's workflows • Automation
Organizational Factors (OF)	OF1: Scope of Innovation strategy	• Innovating of the OARC department • Innovating of radiotherapy clinic/network
	OF2: Set-up of clinic	• Single-site • Multi-site
	OF3: OARC responsibility	• Radiation therapy technologist • Physicists • Radiation therapists • External parties (e.g. students)
	OF4: Implemen-tation strategy	• Structured change management approach ○ Management support ○ Definition of implementation leader ○ Evaluation of quality of contours ○ Establishment of guidelines for usage ○ Education of users ○ Step-wise roll out ○ Adaptation of existing processes and workflows
Individual Factors (IF)	IF1: Mindset	• Plug and Play approach • Entrepreneurial mindset ○ Openness ○ Curiosity ○ Trust
	IF2: Background	• Technical expertise • Algorithmic expertise • Experience in driving change

authors' own work.