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Valuing Digital Health: Using Stakeholder Preferences to Inform the Evaluation of Digital Health Maturity

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under the supervision of
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CERTIFICATE OF ORIGINAL AUTHORSHIP

I, Milena Lewandowska, declare that this thesis is submitted in fulfilment of the requirements for the award of Doctor of Philosophy in the Faculty of Health, at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis. This document has not been submitted for qualifications at any other academic institution.

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Contents

Tables

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Abbreviations

ADHA	Australian Digital Health Agency
AHPRA	Australian Health Practitioner Regulation Agency
AI	Artificial Intelligence
AIC	Akaike Information Criterion
AIHW	Australian Institute of Health and Welfare
AIaMD	AI as a Medical Device
BIBD	balanced incomplete block design
BIC	Bayesian Information Criterion
BWS	Best–Worst Scaling
CBA	Cost–Benefit Analysis
CCA	Cost-Consequence Analysis
CEA	Cost-Effectiveness analysis
CHEERS	Consolidated Health Economic Evaluation Reporting Standards
CI	Confidence Interval
CMA	Cost-Minimisation Analysis
CMM	Capability Maturity Models
CT	Computer tomography
CUA	Cost-Utility Analysis
DCE	Discrete Choice Experiment
DES	Discrete Event Simulation
DHCRC	Digital Health Cooperative Research Centre
DHI	Digital Health Indicator
DHMA	Digital Health Maturity Assessment
DHT	Digital Health Technology
DL	Deep Learning
EE	Economic evaluation
EQ-5D	EuroQol 5-Dimension Questionnaire
EU	European Union
FDA	Food and Drug Administration
GMNL	Generalised Multinomial Logit
HCP	Health Care Professional
HIMSS	Healthcare Information and Management Systems Society
HREC	Human Research Ethics Committee
HRQoL	Health-Related Quality of Life
HTA	Health Technology Assessment
ICT	Information and Communication Technologies
ISPOR	International Society for Pharmacoeconomics and Outcomes Research / Professional Society for Health Economics and Outcomes Research
IT	Information technology
LC	Latent Class
LLM	Large language model
MARS	Mobile App Rating Scale
MAUQ	mHealth Apps Usability Questionnaire
MDR	Medical Device Regulation
ML	Machine Learning
MNL	Multinomial Logit
MSAC	Medical Services Advisory Committee
MXL	Mixed Logit Model
NDHS	National Digital Health Strategy
NLP	Natural Language Processing
OAR	Organs at Risk
OR	Odds Ratio
PBAC	Pharmaceutical Benefits Advisory Committee

PBS	Pharmaceutical Benefits Scheme
PICO	Patient Intervention Comparator Outcome
QALY	Quality-adjusted life years
QoL	Quality of life
RCT	Randomised Controlled Trial
RT	Radiation Therapy
RWE	Real-World Evidence
SD	Standard Deviation
SE	Standard Error
SG	Standard gamble
SLHD	Sydney Local Health District
SP	Stated Preference
SaMD	Software as a Medical Device
TGA	Therapeutic Goods Administration [Australia – confirm]
TTO	Time-trade-off
VAS	Visual Analogue Scale
VIH	Value in Health
WHO	World Health Organisation
WTP	Willingness to Pay

Research output

Conference presentations

Lewandowska M, Street D, Yim J, Jones S, Viney R. Preferences for Adopting Artificial Intelligence in Radiation Therapy Treatment: A Discrete Choice Experiment. Value Health. 2026 Feb;29(2):267-276. doi: 10.1016/j.jval.2025.09.013. Epub 2025 Sep 25. PMID: 41015332

- International Academy of Health Preference Research (IAHPR), 16th Annual Meeting, 29 September–1 October 2025, University of Twente, Netherlands. *Poster presentation*
- The Professional Society for Health Economics and Outcomes Research (ISPOR), Real-World Evidence Summit 2025, 28-30 September 2025, Tokyo, Japan. *Poster presentation*
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Lewandowska M, Street D, Thomas M, Viney R. Evaluation of the Australian National Digital Health Strategy Using Best–Worst Scaling.

- International Academy of Health Preference Research (IAHPR), 16th Annual Meeting, 29 September–1 October 2025, University of Twente, Netherlands. *Brief oral presentation.*

Lewandowska M, Street D, Yim J, Jones S, Viney R. Artificial intelligence in radiation therapy treatment planning: A discrete choice experiment. J Med Radiat Sci. 2024 Dec 20. doi: 10.1002/jmrs.843. Epub ahead of print. PMID: 39705152

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Publications from this thesis

Chapter 3

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Chapter 5

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Chapter 6

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Abstract

Digital maturity in healthcare reflects an organisation's capacity to effectively leverage technology, transform operational processes, and generate value through innovative digital solutions. As healthcare systems increasingly integrate digital technologies, there is a growing need for robust evaluation methodologies that assess not only clinical efficacy and economic impact but also alignment with stakeholder values. This thesis investigates how value is attributed to digital health technologies, with a particular focus on artificial intelligence (AI) in oncology. The traditional economic evaluation frameworks often fall short in capturing the dynamic, user-centred, and system-wide impacts of digital innovations. To explore these limitations, a scoping review of economic evaluations of AI in oncology was conducted. The review identified key challenges, including the rapidly evolving nature of AI, an overreliance on accuracy metrics rather than clinical effectiveness, and insufficient consideration of implementation and equity. A critical gap emerged: the need for value assessments that incorporate stakeholder perspectives, particularly within the Australian healthcare context.

To address this gap, the thesis employs discrete choice experiments (DCEs) to elicit stakeholder preferences beyond conventional clinical and economic metrics. Two empirical studies were conducted in the context of radiation oncology. The first, involving healthcare professionals, revealed strong preferences for AI systems that enhance accuracy and efficiency, with a preference for assistive over fully autonomous systems, especially those offering basic decision explanations. The second study, involving patients and the general public, confirmed the importance of accuracy but also highlighted the value placed on timely care and clinician involvement in AI-supported treatment. These findings underscore the importance of aligning AI development with user values such as autonomy, explainability, and equity.

The final empirical study focuses on the Australian National Digital Health Strategy (NDHS), selected for its policy relevance and alignment with national digital health priorities. Using a Best-Worst Scaling (BWS) approach, the study assessed stakeholder priorities across NDHS initiatives. Results showed that cybersecurity and access to healthcare information were most valued, while emerging technologies like AI were ranked lower. These insights provide actionable guidance for prioritising digital health initiatives that are sustainable, inclusive, and person-centred.

This thesis contributes to the evolving discourse on digital health value assessment by highlighting the limitations of traditional economic evaluation frameworks in capturing the multifaceted

impacts of digital technologies. It demonstrates the utility of stated-preference methods, such as DCEs and BWS, in assessing the value of digital health innovations.

The empirical findings provide evidence on stakeholder preferences for AI in oncology and national digital health priorities in Australia, offering practical recommendations for aligning digital health strategies with user values. By integrating stakeholder perspectives into value assessments, this research supports more responsible, effective, and equitable implementation of digital health technologies in healthcare systems.

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Chapter 1: Introduction

Healthcare systems globally are under increasing pressure due to population ageing, environmental changes, and the growing burden of chronic and infectious diseases. In response, digital health technologies are emerging as promising tools to improve access to care, enhance patient monitoring, and support more efficient and responsive public health systems. However, despite their potential, the evaluation and adoption of digital health technologies remain challenging. This is due in part to their rapid evolution, and the complexity arising from their multidimensional nature including technological, organisational, and user-level readiness.

The overarching aim of this PhD research is to investigate how to define and value digital health maturity, and to explore approaches for evaluating the health economic impact of adopting digital health technologies. While digital health maturity is often measured through technical infrastructure and interoperability, a truly mature system is one that successfully translates these capabilities into realised value for its users. Digital maturity extends beyond systems readiness, including infrastructure and organisational capability, to demonstrated utility for the consumers. Stated preference methods are therefore essential to this aim, as they provide the empirical framework to quantify what users value most, by allowing maturity to be defined not just by what a system can do, but by the extent to which it meets the prioritised needs and preferences of stakeholders.

The research takes a case study approach to generate context-specific insights into how digital health value is perceived and measured in practice. Three empirical studies were conducted using stated preference (SP) methods to elicit stakeholder preferences, including best-worst scaling (BWS) and discrete choice experiments (DCEs). These methods provide a structured way to capture how different groups, including healthcare providers, patients, and policymakers, assess the value of digital innovations.

Two key case studies are examined: the application of artificial intelligence (AI) in radiation oncology, and the implementation of the Australian National Digital Health Strategy (NDHS). These cases were selected not only for their strategic importance in enhancing digital maturity, but also for their relevance across domains such as governance, interoperability, and workforce capability.

Recent advancements in AI technologies have shown significant potential in oncology, where accurate, timely, and detailed interpretation of medical images is critical throughout the cancer care continuum, from early detection to treatment planning and monitoring (Mun and Dieterich 2023).

Adoption of AI in radiation therapy provides a particularly valuable perspective through which to study digital health adoption. It has the potential to improve accuracy, efficiency, and consistency in image interpretation and clinical decision-making, which are the key factors in enhancing the quality and accessibility of cancer treatment (Khalifa and Albadawy 2024).

Yet, implementation of AI faces barriers related to funding, clinical workflows, infrastructure, and stakeholder trust. These challenges reflect broader systemic factors that influence implementation of digital health technologies, such as the availability of technical infrastructure, sustainable funding, and skilled personnel, all of which are shaped by the level of digital health maturity within a given setting (Mennella et al. 2024). Digital health maturity reflects how well-equipped a healthcare system is to adopt and integrate digital innovations, and higher levels of maturity are associated with greater capacity to support the effective deployment of AI in clinical practice (Holmström 2022).

Due to the evolving nature of AI systems, it is important to gain a deeper understanding of the perceptions and needs of stakeholders affected by these systems, including healthcare providers, patients, and caregivers. The first two empirical studies (Chapters 5 and 6) explore preferences related to AI adoption in radiation therapy, identifying what attributes are most valued by patients and providers. The third study (Chapter 7) focuses on the NDHS, assessing preferences for a range of digital health initiatives and offering a broader perspective on how national strategies can support digital health maturity (ADHA 2023a). The case study approach adopted in this thesis allows the generation of both specific and generalisable insights. The findings provide important context for critical considerations relevant to the development, implementation, and evaluation of digital health technologies (DHTs).

This chapter introduces the key concepts of digital health and digital health maturity, exploring their definitions, significance, and methods of measurement. It establishes the context for the case studies and empirical investigations that follow. Chapters 2 and 3 present a critical review of existing evaluation frameworks, highlighting their limitations in capturing the multidimensional value of digital health innovations and the need for more comprehensive and adaptive methodologies. Chapter 4 outlines the theoretical foundations for the SP methods employed in this thesis, which are then applied in the empirical analyses presented in Chapters 5 through Chapter 7. Finally, Chapter 8 discusses the key findings and their implications for future research and policy.

Digital health technology

The term digital health was first introduced by Seth Frank in 2000 and primarily referred to internet-based applications and media aimed at enhancing medical content, commerce, and connectivity (Frank 2000).

The World Health Organisation (WHO) defines digital health as “the systematic application of information and communications technologies, computer science, and data to support informed decision-making by individuals, the health workforce, and health systems, to strengthen resilience to disease and improve health and wellness ” (World Health Organization (WHO) 2020).

The European Commission describes digital health as “tools and services that use information and communication technologies (ICTs) to improve prevention, diagnosis, treatment, monitoring and management of health-related issues and to monitor and manage lifestyle-habits that impact health” (European Commission 2023).

The Food and Drug Administration (FDA) in the USA defines digital health as the “wide range of technologies including mobile health (mHealth), health information technology (IT), wearable devices, telehealth and telemedicine, and personalised medicine, clinical decision support systems, AI and machine learning, that have the vast potential to improve our ability to accurately diagnose and treat disease and to enhance the delivery of health care for the individual” (FDA 2020).

The Australian Department of Health, Disability and Ageing defines digital health as “the use of technology to improve the healthcare system for both patients and providers. This includes telehealth, electronic patient records, electronic prescriptions, healthcare identifiers, electronic referrals, electronic medication charts, and access to trusted data” (Australian Government Department of Health 2021).

While the core concept of utilising digital technologies in healthcare remains consistent across these definitions, they vary in terms of the level of detail, inclusion of specific technologies, or the focus on certain aspects of digital health such as perceived benefits, emphasis on specific digital technologies or perspectives of different stakeholders.

Digital health technologies hold significant promise in addressing critical challenges faced by modern healthcare systems, particularly in improving the quality, efficiency, and accessibility of care. This rapidly evolving field is inherently multidisciplinary, integrating innovations from genomics, mobile health applications, electronic prescribing, electronic health records, and wearable devices (Mathews et al. 2019). Advancements in complementary domains such as AI, big data analytics, and genomics have further accelerated the impact of digital health (Gentili et al. 2022).

Among these, AI stands out as one of the most transformative and rapidly advancing technologies in digital health. It is increasingly used to enhance clinical decision-making, automate administrative tasks, and derive insights from large-scale health data. A variety of AI technologies, such as machine learning (ML), deep learning (DL), and natural language processing (NLP), are increasingly being applied in predictive analytics, diagnostics, and personalised medicine (Alowais et al. 2023). Practical applications include AI-powered medical scribing tools that reduce documentation burdens (AHPRA 2025), as well as systems for interpreting medical images, detecting disease patterns, and supporting clinical decisions (Alowais et al. 2023; Davenport and Kalakota 2019; 2019).

Successful implementation of DHTs, such as AI, in clinical settings depends on robust digital infrastructure, standardised data practices, and mature health information systems capable of capturing, sharing, and utilising clinical data at scale. Adoption of AI-technologies in healthcare illustrate the broader challenges of integrating digital health tools, highlighting that the barriers are not only technical but also structural and systemic. In this context, assessing digital health system maturity becomes essential, helping to identify strengths and gaps, and guiding strategic investments toward more integrated, efficient, and responsive digital healthcare environments. Given the recent transformative advancements in AI technologies, and the distinct challenges associated with its use in healthcare, the application of AI in this sector was chosen as the focus for developing two empirical studies (Chapters 5 and 6). These studies demonstrate the value of adopting AI technologies in healthcare settings.

The next section of this thesis examines digital health maturity frameworks, which provide structured tools to assess how effectively health systems, organisations, or services use digital technologies in care delivery. These frameworks support evaluation of digital capabilities, identify areas for improvement, and enable benchmarking based on outcomes such as efficiency, clinical performance, and user satisfaction.

Digital health maturity assessment

Digital transformation in healthcare depends not only on the adoption of emerging technologies, such as AI, but also on the health system's ability to integrate these tools into everyday practice in a meaningful and sustained way. This requires more than isolated technological upgrades. It requires a clear understanding of existing digital capabilities and a structured approach to measuring and improving them over time (Stoumpos et al. 2023). This is where digital health maturity becomes critical. Defined as the extent to which digital systems are used to support high-quality care, digital maturity provides a framework for assessing how well an organisation is positioned to achieve digital transformation (Duncan et al. 2022; Snowdon et al. 2024). It reflects a combination of technological infrastructure, workforce skills, digital literacy, and organisational readiness (Martin et al. 2019). Importantly, digital maturity is shaped by and contributes to the broader digital ecosystem, which connects data sources, applications, and technologies across the health sector (Iyawa et al. 2016). A mature digital environment allows this ecosystem to function cohesively, enabling health services to innovate, scale, and continuously improve (Stoumpos et al. 2023).

Foundational digital infrastructure is essential for the successful implementation and uptake of digital health initiatives across healthcare systems and settings. The importance of digital infrastructure was highlighted during the COVID-19 pandemic, when DHTs were rapidly deployed for contact tracing, public health communication, and quarantine management (Labrique 2025). While this rapid rollout demonstrated the potential of digital solutions in crisis response, it also revealed critical gaps in evaluation frameworks and infrastructure readiness. These gaps may also impact on the successful integration of more complex technologies, such as AI in healthcare, which depends on robust digital infrastructure, standardised data governance practices, and mature health information systems. Addressing these foundational requirements is important not only for the immediate adoption of DHTs but also for their integration into routine healthcare delivery.

Identifying and addressing infrastructure gaps is therefore a strategic priority. Ensuring digital health solutions are fit for purpose and effectively adopted requires strong governance frameworks to guide technical development, alongside engagement from stakeholders, including technology vendors, healthcare providers, patients, and policymakers. In this context, structured assessments of digital health maturity provide a comprehensive understanding of existing capabilities, gaps, and priority areas., which can be used to inform strategic planning and policy development (Koutsoukis 2025).

Digital health maturity assessment models serve as tools for advancing technological capabilities within healthcare organisations. By providing structured frameworks to assess organisational readiness, these models inform both the development and evaluation of comprehensive digital health strategies throughout their implementation lifecycle (Woods et al. 2022). They enable healthcare organisations to benchmark capabilities, identify improvement opportunities, and strategically plan digital transformation initiatives that align with broader organisational objectives.

The digital health maturity models can be divided into three categories (Fraser et al. 2002):

- The Capability Maturity Models (CMM)
- Hybrid-like and Likert-scale like questionnaires
- Maturity grids

Capability Maturity Models are a methodology used to develop and refine an organisation's software development process as an evolutionary path of increasingly organised and systematically more mature processes. The CMM group of models are structured according to a formal architecture where each process area is organised by common features that specify a number of key practices to address a series of goals. These models adhere to a standardised format and are frequently employed for the purpose of certification (van Dyk and Cornelius 2013).

The Likert-like questionnaires represent a simple form of maturity assessment, in which the respondent is asked to score the relative performance of the organisation on a multi-point scale. The focus of Likert-like questionnaires is to provide indication of good practice rather than an overall assessment of maturity (Fraser et al. 2002).

The maturity grid is typically used for self-assessment purposes and as a part of framework for improvement. However, unlike Likert-like questionnaires, maturity grids contain text descriptions for each activity at each maturity level, for each of several aspects of the area under study. It is a matrix that shows different stages of an organisation's progress towards digital health maturity (van Dyk and Cornelius 2013). The following paragraphs provide examples of models used to assess the digital maturity of healthcare organisations along with a discussion of their limitations.

Healthcare Information and Management Systems Society (HIMSS)

HIMSS has developed a set of maturity models that provide a framework for assessing and advancing the process of digital maturity within healthcare organisations. The HIMSS maturity models are examples of maturity grids (van Dyk and Cornelius 2013; Cresswell et al. 2019). HIMSS digital health indicator (DHI) measures progress towards a digital health ecosystem (i.e., a system that connects clinicians and health providers with patients, enabling them to manage their health and wellbeing through the use of digital tools in a secure and private environment). It consists of four dimensions that aim at advancing organisations digital health transformation (Table 1.1).

Table 1.1: Digital health indicator

Dimension	Description
Interoperability: (i.e. foundational, structural, organisational and semantic)	The ability of different information systems, devices, and applications to access, exchange, integrate and cooperatively use data in a coordinated manner, within and across organisational, regional and national boundaries, to provide timely and seamless portability of information and optimise the health of individuals and populations globally
Person-Enabled Health	Health system ability to meet and deliver on the individual's needs, values, and personalised health goals. Measures of person-enabled care include the level of personalisation of care, proactive risk management and ability to apply predictive systems informed by robust data analytics and digital health technology infrastructure
Predictive analytics	The transformation of data into knowledge and use of real-world insights to inform decision making. This may include tracking and tracing of data to identify risks for potential harm or poor outcomes, use of personalised data tailored to individual health and wellness (e.g., genomic, biometric data) and operational analytics that mobilise data to track health system performance outcomes (e.g., supply chain, financial and adverse events)
Governance and workforce	The strategic leadership and oversight of digital health systems that ensures the policy and regulatory environment of health systems ensures privacy, security, stewardship and accountability.

Source: HIMSS (2025)

The DHI assessment is based on an online survey completed by healthcare organisations and their representatives (e.g. hospitals, and hospital executives) by self-assessing their performance against each indicator using a 5-point Likert scale (HIMSS 2023). To calculate a comprehensive score for the four dimensions of digital health, the HIMSS proprietary scoring methodology is used to generate a score out of 400, each of the four dimensions of the DHI account for 100 points (HIMSS 2025) (HIMSS 2025). The indicator responses reflect the percentage of programs or clinical services that have a achieved each digital indicator or outcome within an organisation or across a health system (Table 1.2).

Table 1.2: Digital health indicator scoring scale

Score	Result	Definition
0%	Not Enabled	The capabilities referenced in the indicator statements are not typically or are only rarely available
1-25%	Minimally Enabled	The capabilities referenced in the indicator statements are available in a limited manner
26-49%	Somewhat Enabled	The capabilities referenced in the indicator statements are available roughly half the time;
50-94%	Mostly Enabled	The capabilities referenced in the indicator statements are generally available most of the time
95-100%	Fully Enabled	The capabilities referenced in the indicator statements are almost always or always available

Source: HIMSS (2025)

In addition to DHI, HIMSS developed seven maturity models for assessment of healthcare organisation digital maturity focusing on specific domains of healthcare (Table 1.3). These models provide prescriptive frameworks for healthcare organisations to build their digital health ecosystems within a specified area.

Table 1.3: HIMSS models of assessment of digital health maturity

EMRAM	The Electronic Medical Record Adoption Model is a roadmap for assessing and advancing the adoption and utilisation of EMRs (Reddy et al. 2023)
AMAM	The Analytic Maturity Assessment Model focuses on driving the clinical, operational, and financial analytics efforts to align with and support organisational strategy (HIMSS 2023)
C-COMM	The Community Care Outcomes Maturity Model assesses digital maturity in non-acute facilities to guide and inform the unique needs and features of care delivery in a community organisation (HIMSS 2023)
CCMM	The Continuity of Care Maturity Model focuses on building and improving critical capabilities needed for coordinated patient care and knowledge driven community of care (HIMSS 2023)
DIAM	The Digital Imaging Adoption Model assesses a health system's IT-supported digital imaging processes to identify and guide the right digital imaging strategy for improved patient health outcomes (HIMSS 2023);
INFRAM	The Infrastructure Adoption Model assesses and maps the technology infrastructure capabilities required to reach clinical and operational goals while meeting international benchmarks and standards (HIMSS 2023)
CISOM	The Clinically Integrated Supply Outcomes Model is a prescriptive pathway toward improving supply chain infrastructure to boost quality, safety and efficacy (HIMSS 2023).

Source: HIMSS (2025)

The HIMSS assessments are notable for its comprehensive coverage of digital health maturity domains, including interoperability, data security, clinical decision support, and patient engagement. However, its association with health outcomes has been mixed. Von Poelgeest et al. (2017) found that patients in Dutch hospitals which had higher EMRAM scores had shorter lengths of stay after colorectal cancer surgery (van Poelgeest et al. 2017). In contrast, Martin et al. (2019) found no link between digital maturity and broader hospital performance indicators such as mortality, readmissions, or complications (Martin et al. 2019). Another study based on HIMSS EMRAM Maturity Model data to measure digital maturity, used cross sectional design to investigate the impact of digital maturity on quality outcomes and patient experience in United States (US) hospitals. The results showed that advanced digital maturity in US hospitals was associated with stronger patient experience outcomes (i.e. communication with doctors, nurses and communication about medicines and therapies) (Snowdon et al. 2024). Criticisms of the HIMSS model include its heavy emphasis on technological functionality over human and organisational factors, and its limited capacity to contextualise digital tools as enablers of transformation (Cresswell et al. 2019).

Other models to assess digital maturity include Victoria's Digital Health Maturity Model (VDMM) and Gippsland Primary Health Network's Digital Health Maturity Assessment (DHMA) (Reddy et al. 2023) used for the assessment of digital maturity in general practice (Ernst&Young 2022), the Informatics Capability Maturity (ICM) model used to describe health organisations performance in terms of collection, management, sharing of information (Liaw et al. 2017) and Tele-Medicine Service Maturity Model (TMSMM) used to measure and manage the maturity of telemedicine processes (van Dyk and Cornelius 2013).

While digital maturity assessment constitutes an essential component of comprehensive value evaluation, it is important to recognise that maturity measurement represents an input to value analysis rather than the evaluative process itself. In other words, assessing digital maturity helps to understand the readiness and capacity of a health system to adopt and effectively use digital technologies, but it does not, on its own, determine the actual value delivered.

These models fall short in capturing the experiences, preferences, and priorities of end users, including clinicians, patients, and administrators. Most existing models emphasise technical infrastructure, interoperability, and governance, with less focus on user adoption, perceived value, or quality-of-care outcomes (Duncan et al. 2022). Conventional survey approaches using Likert-type scales, typically employing five-point scales ranging from "Strongly Disagree" to "Strongly Agree", are increasingly recognised as inadequate for assessing multifaceted digital health strategies, particularly when confronting the complexity and breadth of national digital health initiatives (Steenkamp et al. 2025).

Overall, maturity assessment frameworks can be valuable tools for guiding strategic planning and supporting organisational transformation toward digitally enabled healthcare. Maturity assessments play important role in informing strategic development and support organisational self-assessment by identifying capability gaps and allowing organisations to track the progress toward digital health maturity. For example, the HIMSS DHI model has also been previously used to guide the development of digital health strategies and inform investment decisions within Australian contexts, including the Queensland Digital Health Strategy (Queensland Government 2017) and the Sydney Local Health District (SLHD) Digital Health Strategy (Sydney Local Health District 2022). Research evaluating digital health capability in Queensland has further demonstrated how the DHI model can support evidence-based planning and prioritisation of digital health initiatives (Woods et al. 2022).

National digital strategies serve as frameworks for accelerating and managing digital health maturity across healthcare ecosystems. By establishing clear governance structures, interoperability standards, and implementation roadmaps, these strategies aim to support and guide advancements in digital health maturity (Ibrahim et al. 2022). Strategies outline long-term goals, investment areas, and frameworks for coordinated action across the health sector.

Australian National Digital Health Strategy (NDHS).

This section provides an overview of the Australian NDHS 2023-2028, the Australian Federal Government policy framework that informed the development of one of the empirical studies presented in this thesis. The following discussion establishes the context, key objectives, and governance structures of the NDHS, providing background for understanding the research design and findings presented in Chapter 7. The NDHS was selected as a case study for examining the priority setting of initiatives due to its national significance, structured policy framework, and direct relevance to digital transformation in healthcare. By situating the research within the context of the NDHS, the case study provides insight into how well digital health priorities outlined in the strategy align with the public's preferences and where gaps may exist.

The NDHS identifies opportunities for digital health to support planned national health system reforms and to address the emerging health system challenges. The strategy is guided by the Strategy Delivery Roadmap, setting out priority areas and initiatives (ADHA 2023b). The Strategy Roadmap is organised into strategic priority areas to support four key health system outcomes, these being:

- Digitally enabled healthcare systems, where health and wellbeing services are connected, safe, secure and sustainable. The priority areas within the outcome include "connected care", which aims at moving health systems from siloed clinical document repositories to near real-time data exchange across primary, acute, aged and other care sectors.
- Person-centred systems describe systems where Australians are empowered to look after their health and wellbeing, equipped with the right information and tools. The priority areas within this outcome include support for strong consumer digital health literacy,

increasing availability of health information and improving consent management and flexible health information exchange.

- Inclusive systems represent the health system where Australians have equitable access to health services, when and where they need them. This includes initiatives aimed at improving and expanding virtual care, integrating personal devices and supporting equitable access to health care.
- Data-driven systems are systems where readily available data informs decision making at the individual, community and national levels. This includes use of health information for research and public health purposes, planning for emerging data sources and technology such as AI, spatial data and genomics and use of digital health tools to collect, analyse and report health information.

The initiatives within the Strategy Roadmap were identified through a collaborative process involving various stakeholders (ADHA 2023b). This included consultations with consumers, healthcare providers, industry partners, researchers and government representatives. The roadmap is considered a living document that is periodically reviewed to align with technological developments and emerging policy priorities. Additionally, benchmarking against international best practices and leveraging feedback from healthcare professionals, policymakers, and the public contribute to refining the strategy. The Strategy Roadmap identifies 80 specific initiatives which are divided into the specific priority areas listed above. These initiatives aim to boost digital health adoption by integrating digital solutions, building workforce skills, and helping consumers feel informed and confident using digital tools. The initiatives outlined in the Strategy Roadmap provide the foundational context for one of the empirical studies presented in this thesis, discussed in more detail in Chapter 7.

Regulatory context for digital health and AI: implications for market access, funding and evaluation

This section provides a brief overview of regulatory requirements for digital health in Australia and internationally, with specific reference to legislation and challenges associated with the regulatory assessment of AI technologies. It highlights the complexity of the legal landscape and explores its implications for clinical practice and the development of appropriate evaluation frameworks. This overview provides the context for the discussion on value frameworks presented in Chapter 2.

Regulatory frameworks play a critical role in guiding the development and adoption of DHTs. They define acceptable clinical evidence, shape evaluation methodologies, and influence access to funding and market pathways. As digital health and AI tools become increasingly complex and integral to clinical decision-making, clear and robust regulations are essential to ensure their safe, ethical, and effective integration into healthcare systems. These frameworks also play a key role in shaping investment decisions, as regulatory compliance is often a prerequisite for obtaining funding and entering the market.

An overview of the international guidelines relevant to digital health solutions is presented in Table A1.1, Attachment 1. These include regulations that ensure compliance and safety, standards that underpin regulatory requirements, and specific laws and frameworks related to AI in healthcare. The overview is based on authoritative sources such as:

- The WHO Global Strategy on Digital Health 2020–2025, which promotes robust digital health systems globally (WHO 2021);
- The FDA's guidance on digital health, which provides clarity on regulatory pathways for AI-based medical products (FDA 2025);
- The EU General Data Protection Regulation (GDPR) and the UK GDPR, which safeguard data privacy and personal health information (European Commission 2018; UK Government 2018);
- The Medical Device Regulation (MDR), including software as medical device (SaMD) and AI as medical device (AIaMD) regulations, which govern the safety and performance of digital medical technologies (EUR-Lex 2017);
- The EU Artificial Intelligence Act (2024), which regulates AI based on risk levels to ensure safety and uphold fundamental rights of EU citizens (European Commission 2024).

In Australia, the regulatory landscape is shaped by multiple legislative instruments, including the Therapeutic Goods Act 1989, My Health Records Act 2012, and the Australian Privacy Act 1988, among others. The Therapeutic Goods Administration (TGA) oversees the regulation of medical devices, including software-based technologies and AI-driven tools. The TGA's evolving guidelines, particularly those addressing SaMD, define the types of evidence required for approval and the conditions under which international regulatory decisions may be accepted (Table A1.2, Attachment 1). The Australian Digital Health Agency (ADHA) further supports the integration of digital technologies by developing interoperability standards and providing implementation guidance.

Overall, the regulatory environment for DHTs is fragmented, involving multiple overlapping laws and agencies, and is frequently updated, making it challenging for innovators to navigate. Despite the growing number of regulations, concerns remain about whether it can keep pace with rapid technological advancements. The case of AI in healthcare provides an example of the challenges arising in an evolving regulatory landscape, highlighting the need for flexible and adaptive regulatory models capable of accommodating evolving nature of these technologies.

The EU AI Act, signed in June 2024, is the first binding worldwide regulation on AI, applicable across all EU countries. It aims to ensure AI systems are safe, transparent, traceable, non-discriminatory, and environmentally friendly. The AI Act impacts AI/machine learning-enabled medical devices, diagnostics, and clinical support tools. It follows a risk-based approach, classifying AI systems into minimal, specific transparency, high, and unacceptable risk categories (Table A1.3, Appendix 1). For AI systems that demonstrate high risk, technical documentation is required before the product is placed on the market or taken into use and the technical documentation must be kept up to date. The technical documentation for high-risk AI is comprehensive, including the description of the elements of the AI systems and the process of its development, such as design specification, system architecture, key design choices, rationale and assumptions made, data requirements, training methodology, computational resources used to develop, train and validate the AI system along with validation and testing procedures and performance metrics (Aboy et al. 2024). In addition, the Act poses specific requirements for AI-system transparency and human oversight to ensure safe and ethical deployment. The Act specifies requirements regarding the AI system accuracy, robustness, cybersecurity, and resilience throughout the product lifecycle (Aboy et al. 2024).

The complexity and scope of the EU AI Act pose operationalisation challenges, particularly for manufacturers of AI-based medical technologies, due to the limited access to the institutions like notified bodies which are authorised to assess compliance with regulatory requirements (Palaniappan et al. 2024). These challenges are compounded by the rapid pace of technological change. For example, the definition of the “intended use” of AI-based medical devices may be challenging as AI models are likely to have multiple uses that may not be determined prior to adoption. Compliance with regulatory standards is also resource-intensive, requiring substantial investment in clinical validation, cybersecurity, and documentation costs. This introduces significant cost and time implications for developers, potentially limiting capital-constrained innovators from entering the market while favouring established companies with regulatory expertise, which in turn may have an impact on the price of these technologies (Babina et al. 2024). Overall, these challenges may also impact the type of clinical evidence available to support the implementation of AI technologies, with a greater reliance on real-world evidence (RWE) rather than randomised controlled trials (RCTs), which remain the gold standard in clinical research (Hariton and Locascio 2018).

These challenges may collectively impact the ability of DHTs developers to generate the necessary evidence for approval and to secure the funding required for development and deployment. The following chapter provides an overview of the value framework used to assess DHTs. It also explores how the potential impact of the regulatory challenges outlined in the previous section may influence the evaluation process, shaping the types of evidence considered and the overall approach to assessment.

Overview of the thesis components- structural outline

Building on the context provided in Chapter 1 and recognising the unique challenges associated with assessing the value of digital health initiatives, this thesis examines these issues further in Chapter 2, which explores relevant value assessment frameworks. This is followed by Chapter 3, which investigates the published literature on methods used to assess the economic value of digital health. The core of the thesis comprises three stated preference experiments. Chapter 4 describes the methods, rationale, and development of two DCEs and one BWS study. Chapters 5 and 6 present the two DCEs, which build on a shared context but assess preferences from the perspectives of consumers and healthcare professionals, two groups whose acceptance is critical for successful adoption. Chapter 7 reports the BWS survey on consumers' preferences for implementing digital health initiatives within the NDHS. This work is highly relevant to the Australian healthcare sector, where digital health initiatives are a key pathway to improving care delivery. Chapter 8 synthesises the findings and discusses their policy implications for valuing and implementing digital health initiatives in the Australian healthcare sector.

Chapter 2: Value framework for assessment of digital health technologies

Digital health technologies (DHTs) are transforming healthcare delivery, yet their integration into existing health systems requires rigorous evaluation through established frameworks. Healthcare decision makers require a systematic assessment of the value proposition for DHTs and of the return on investment that is required to justify the costs of implementing digital health initiatives (Wilkinson et al. 2023). This economic justification is important as organisations face competing priorities and limited resources in an increasingly complex healthcare landscape. Health interventions are assessed not only based on their ability to improve clinical outcomes, but also on their effects on patient experience, workforce sustainability, and long-term system performance. In this context, decision-makers must rely on evaluative approaches that can accommodate multiple, often competing, dimensions of value.

The Quadruple Aim provides a widely adopted framework focusing on four key goals for improving health systems: improving population health, enhancing patient experience of care, reducing costs, and supporting the wellbeing of healthcare providers (Duncan et al. 2022). While the Quadruple Aim offers a clear statement of what healthcare systems seek to achieve, it does not prescribe how these objectives should be measured or balanced in practice. Translating these system-level goals into operational decision-making therefore requires robust analytical frameworks.

Value frameworks are tools that guide decision-makers in determining the worth of health technologies. They encompass a range of methodologies, from Health Technology Assessment (HTA) and economic evaluations to specific frameworks for assessment of digital health maturity, which may inform value frameworks (Woods et al. 2022). By systematically evaluating the clinical, economic, and organisational aspects of DHTs, these frameworks help stakeholders make informed choices about adoption, implementation, and scaling.

To understand how health technologies are assessed and funded in Australia, this chapter provides an overview of the standard evaluation frameworks currently in use for evaluation of heath technologies such as medicines, medical devices and health services, followed by a discussion of why these frameworks may not be well-suited for evaluating DHTs.

Health Technology Assessment

Health technology assessment (HTA) is a multidisciplinary process that evaluates the medical, social, economic, and ethical implications of healthcare interventions, using explicit methods to determine the value of health technology at different points in its lifecycle (Ramezani et al. 2025). It aims to inform decision-making regarding the introduction, reimbursement, and use of health technologies such as pharmaceuticals, medical devices, medical procedures, and health care programs including digital health interventions (Gray 2011).

HTA has emerged as a critical process required by numerous jurisdictions worldwide before providing funding for new medical technologies. Countries including the United Kingdom, Australia, Canada, and many European nations have established HTA bodies that systematically evaluate the clinical effectiveness, cost-effectiveness, and broader societal impacts of innovations before approving their use within public healthcare systems. This mandatory assessment serves as a gateway for innovative technologies and ensures that limited healthcare resources are directed toward solutions that demonstrate meaningful value. The comprehensive nature of modern HTA frameworks provides decision-makers with robust evidence regarding a technology's true impact across multiple dimensions. This is then used to determine whether patients can gain access to these innovations through public funding or insurance coverage pathways.

Economic evaluation in healthcare and digital health technologies.

Economic evaluation is an important part of the HTA process and can be defined as a comparison of alternative options in terms of their costs and consequences (Gray 2011). Healthcare resources are scarce which means the available resources are never sufficient to allow all available health interventions to be provided. Consequently, decision-makers must make choices between the alternatives in a way that maximises the outcomes obtained from them. By prioritising technologies that provide the greatest health benefits within available resources, population health can be optimised.

The main types of full economic evaluations in health care include cost effectiveness (CEA), cost-utility analysis (CUA) and cost-benefit analysis (CBA), all of which take into consideration both costs and consequences of two or more alternatives being compared (Gray 2011). In addition, cost-minimisation analysis (CMA) focuses solely on identifying the cheapest option when outcomes are proven equivalent, while cost-consequence analysis (CCA) presents costs and multiple outcomes separately without aggregation, giving decision-makers flexibility to apply their own value judgments to various outcome measures (Gray 2011).

Cost-effectiveness analysis presents results as a cost per natural unit of effect (e.g., life-years gained, cases detected). It is useful when interventions have comparable outcomes, but this limits its applicability to technologies with broader or non-health outcomes. This may limit the applicability of CEA for evaluation of DHTs, which often influence behavioural, process, or system-level changes not easily captured by clinical endpoints alone (Gray 2011).

Cost-utility analysis extends CEA by combining quality and quantity of life into a single outcome, quality-adjusted life years (QALYs), making it a preferred outcome in many HTA settings for comparing interventions across disease areas. The utility values used in QALY calculations are generally derived from stated preference-based methods, such as time trade-off (TTO), standard gamble (SG), and increasingly, discrete choice experiments (DCEs) (Gray 2011). These techniques elicit individual or population preferences for different health states relative to perfect health, providing the weights necessary to quantify health benefits.

However, DHTs often affect domains such as patient empowerment, and access to care, factors that are not fully captured by traditional preference-based health-related quality of life (HRQoL) instruments. As a result, their value may be underestimated in conventional CUA frameworks (Gomes et al. 2022). Stated preference methods are increasingly being adopted to capture broader value elements that are relevant to DHTs (Gomes et al. 2022; Szinay et al. 2021).

Cost-benefit analysis values both costs and outcomes in monetary terms, facilitating cross-sectoral comparisons (e.g., health vs. education) (Gray 2011). However, placing a dollar value on life or quality of life is ethically contentious, limiting its acceptability in healthcare decision-making (Keller et al. 2021). This also makes it ill-suited to DHTs that deliver benefits that are hard-to-monetise (e.g., improved health literacy or self-management).

Cost-minimisation analysis assumes equivalent outcomes across alternatives and identifies the lowest-cost option. This is only appropriate when clinical equivalence is established, which is rare in the evaluation of innovative or evolving DHTs where evidence is still emerging. CCA reports costs and outcomes in a disaggregated manner, allowing decision-makers to apply their own value judgments. Its flexibility makes it more adaptable to complex interventions, such as DHTs with multidimensional outcomes and stakeholder-specific impacts, but it lacks the formal decision rules of other approaches (Gray 2011).

The economic evaluation frameworks outlined above are used to generate evidence that informs funding decisions for the adoption of health technologies in publicly funded healthcare systems. The following sections explore this process in more detail.

Healthcare funding mechanisms in Australia

In Australia, health services are funded through a mix of state and federal government contributions, private health insurance, and out-of-pocket payments. State governments are responsible for delivering public hospital care, provided free of charge to all Australians as well as community and public health services. Medical services are largely funded through Medicare (Medicare 2025), which is a universal health insurance scheme that covers a broad range of services including general practice, specialist consultations, and diagnostic testing. Medicines are primarily funded through the Pharmaceutical Benefits Scheme (PBS) (PBS 2025b), which subsidises the cost of approved prescription medicines and vaccines to ensure equitable access for all Australians. Funding decisions for both medicines and medical services are informed by expert advisory bodies: the Pharmaceutical Benefits Advisory Committee (PBAC) (PBS 2025a) and the Medical Services Advisory Committee (MSAC) (MSAC 2025). The PBAC evaluates submissions for new medicines to be listed on the PBS, while MSAC assesses new medical services and technologies for public funding under Medicare. Both committees rely on economic evaluations, particularly CUA, CEA, and CMA, to determine whether proposed interventions provide value for money. These assessments are critical in guiding government investment decisions and ensuring that limited healthcare resources are allocated efficiently.

Compared to more established areas of medicines and health services, the digital health landscape in Australia is rapidly evolving (AIHW 2024c). The progress is focused on creating a connected, person-centred system that leverages technology to improve healthcare access, quality and outcomes, guided by the Australian National Digital Health Strategy (ADHA 2023a). The national digital health initiatives are primarily led and funded by the Australian Digital Health Agency (ADHA) (ADHA 2025), which receives federal funding to implement national infrastructure such as My Health Record, secure messaging systems, and interoperability standards. Funding for DHTs spans all levels of the health care system due to the broad scope of these initiatives, which may form part of health service delivery, pharmacological therapy or foundational investments needed to support healthcare delivery. This funding also includes targeted budget allocations for innovation, infrastructure upgrades, and integration across care settings (ADHA 2025). In some cases, DHTs, particularly those classified as medical devices or used in conjunction with pharmaceuticals, such as biomarker-based digital tools, may be subject to health technology assessment (HTA) and require regulatory approval through the Therapeutic Goods Administration (TGA) before being eligible for public funding or inclusion in the Medicare Benefits Schedule (MBS) (Motahari-Nezhad et al. 2022). However, not all DHTs pursue or qualify for MBS reimbursement, especially tools like mobile health apps, AI-based software, or patient engagement platforms (Australian Epilepsy Project 2025). In such cases, assessment and funding is more fragmented and inconsistent. Some of these technologies may be evaluated by state health departments, research institutions, or innovation bodies like the Digital Health Cooperative Research Centre (DHCRC) or CSIRO, often within the context of pilot studies, grants, or procurement trials. These assessments are not always standardised or made publicly available. Moreover, many digital solutions, particularly low-risk or consumer-facing tools, may bypass formal HTA altogether, instead gaining adoption through public-private partnerships, competitive grants, or direct procurement by health services. Private health insurers may also adopt digital tools independently, based on internal evaluations rather than national HTA frameworks. This fragmented landscape reflects both the rapid pace of innovation and the limitations of traditional HTA models, which are not always suited to the iterative nature of digital technologies.

The next section of this chapter explores the distinct challenges and methodological differences involved in conducting economic evaluations of DHTs, as compared to traditional assessments of health interventions such as pharmaceuticals, and medical services. By identifying these unique characteristics, the discussion aims to highlight critical gaps in existing value assessment frameworks that limit their applicability to digital health solutions. Recognising these limitations is essential for understanding the rationale behind the methodological choices made in this thesis.

Methodological challenges in evaluating digital health technologies

While conventional economic evaluation methods provide valuable frameworks for assessing healthcare interventions, they present limitations when applied to digital health interventions. While DHTs often fall under the broader umbrella of medical services, sharing the inherent complexities of evaluating non-pharmacological health service delivery, they also introduce distinct methodological challenges. Unlike standard pharmaceutical medications or standalone medical devices, the evaluation of DHTs within a health service context requires nuanced considerations regarding the type of evaluation applied. These complexities involve specific parameters such as the choice of perspective, the selection of appropriate service-level comparators, and the identification of multifaceted outcome measures that may capture both direct clinical costs and broader systemic benefits. (Table 2.1; (Gomes et al. 2022).

Table 2.1: Key factors differentiating economic evaluation of pharmaceuticals, medical devices and digital health interventions

Item	Pharmaceuticals	Medical devices	Digital health interventions
Comparator	Usually a well-defined comparator, e.g., placebo	Usually a well-defined comparator, e.g., competing device	Often a combination of alternative treatment options
Product evolvement	Fixed	Gradual: product likely to evolve over time with modifications/iterations	Fast: user feedback is used in a co-design process resulting in frequent updates
User involvement	Limited to compliance	Some assessment of interaction between user and the device may be required	Active user involvement
Intervention cost	High fixed costs (R&D, manufacturing). - Variable cost per dose. - Cost per patient may decrease with scale.	- Fixed costs (R&D, manufacturing). - Variable costs per unit. - Cost per patient may decrease with scale.	- Fixed development or sunk costs. - Marginal cost per additional user often low or zero. - High scalability.
Benefit assessment	Health-related outcomes	Health-related outcomes, Non- health benefits for some products	Diffused health and non-health changes i.e., experience, satisfaction, access

Source: Adapted based on Table 1, (Gomes et al. 2022)

The economic evaluation of pharmaceuticals and medical devices is mostly conducted from healthcare sector perspective where the benefits are measured in terms of improvement in health and health-related quality of life. The choice of comparator is informed by clinical settings, current standard of care and the intended patient population in which the treatments will be used. Digital health interventions introduce some practical challenges for evaluation, primarily because they often involve complex, multi-component interventions. In some cases, isolating the effects of specific digital component from the other inputs can be difficult (Gomes et al. 2022). The choice of comparator may vary. For process based DHTs, the comparator is often the existing standard of care, in other cases, it may be another digital tool or combination of interventions. It is important to consult clinical experts during the design of any evaluation plan to ensure potential "spillover" effects of the DHT are adequately considered (Malcolm 2025). At the health system level, DHT can improve care coordination, information flow, and clinical decision-making, leading to productivity gains, reduced duplication of services, and more efficient use of workforce and infrastructure (Productivity Commission 2024). For patients and caregivers, spillover effects may include reduced travel and waiting times, improved access to care, enhanced self-management, and reduced informal care burden, which may translate into time savings and quality-of-life benefits (Gentili et al. 2022). Digital health can also produce broader societal spillovers, such as improved data for population health planning, strengthened public health surveillance, and accelerated innovation through shared learning and wider adoption across services (Gentili et al. 2022). These indirect and system-wide effects are often diffuse, accrue over time, and fall outside traditional cost and outcome boundaries, making them challenging to quantify within conventional economic evaluation frameworks.

Another consideration relates to the target population. Unlike pharmaceuticals, which are typically defined by the therapeutic indication, DHTs may be deployed across broader or more heterogenous populations (Malcolm 2025). They can affect multiple stakeholders within the healthcare ecosystem, including providers to patients to payers. Consequently, evidence generation should aim to include broader and more representative populations and account for potential shifts or distortions in patient pathways, which may affect study design and data collection (Malcolm 2025).

DHTs often generate multidimensional outcomes that extend beyond traditional clinical endpoints, encompassing aspects such as accessibility, convenience, user engagement, and data-driven insights (Gomes et al. 2022). While some of these outcomes may ultimately impact health-related endpoints such as QALYs, through improved adherence, better self-management or healthier behaviour (Kolasa and Kozinski 2020), they may also include broader range of system-level or societal benefits, such as efficiency gains, quality of care improvements, patient and provider satisfaction, and societal impacts (i.e. social inclusion, productivity and impact on natural environment).

However, rather than describing DHTs as intrinsically “different”, the key question for evaluation is how these additional effects should shape the design of the study and the selection of outcomes. For instance, it may be appropriate to focus on intermediate outcomes, such as adoption, engagement, or adherence, as proxies for final health outcomes, particularly when the link to long-term health effects is uncertain. In this sense, the evaluation challenge is less about whether DHTs have unique value and more about defining the Patient Intervention Comparator Outcome (PICO)- framework appropriately and choosing outcomes that meaningfully capture the intervention’s impact.

Examples of non-utility-based tools for assessment of DHTs, which can complement economic evaluation or inform early stage and implementation research include mobile app rating scale (MARS) (Klug 2024), telemedicine usability questionnaire (TUQ) (Hajesmaeel-Gohari and Bahaadinbeigy 2021) and system usability scale (SUS) (Hyzy et al. 2022). However, as these tools assess user experience, usability, or satisfaction, the extent to which these factors correlate with clinical effectiveness or long-term health outcomes and quality of life remains unclear. Additionally, their generalisability is often limited due to their context-specific nature. The practice of fitting a statistical model to health utility data referred to as “mapping” can be applied to estimate the effect of intervention in terms of health utility, subsequently used to calculate QALYs (Wailoo et al. 2017). While the existing literature has primarily focused on mapping between health-related outcome instruments, in principle similar approaches could be adapted to explore the mapping of non-health or experiential measures onto health outcomes, including utilities if appropriate data are available. This is an important area for future research (Spertus et al. 2020).

Clinical outcomes associated with digital health interventions, and medical devices more generally, often depend on the training, competence, and experience of the end users. Although the active involvement of users provides benefits such as improved experience and higher adoption, it may trigger additional costs such as facilitation costs and opportunity costs of user time spent on training and pilot testing. Hence, costs of DHTs often comprise of both procurement costs and costs of infrastructure as well as operative costs related to maintenance and upgrades (Tarricone et al. 2017).

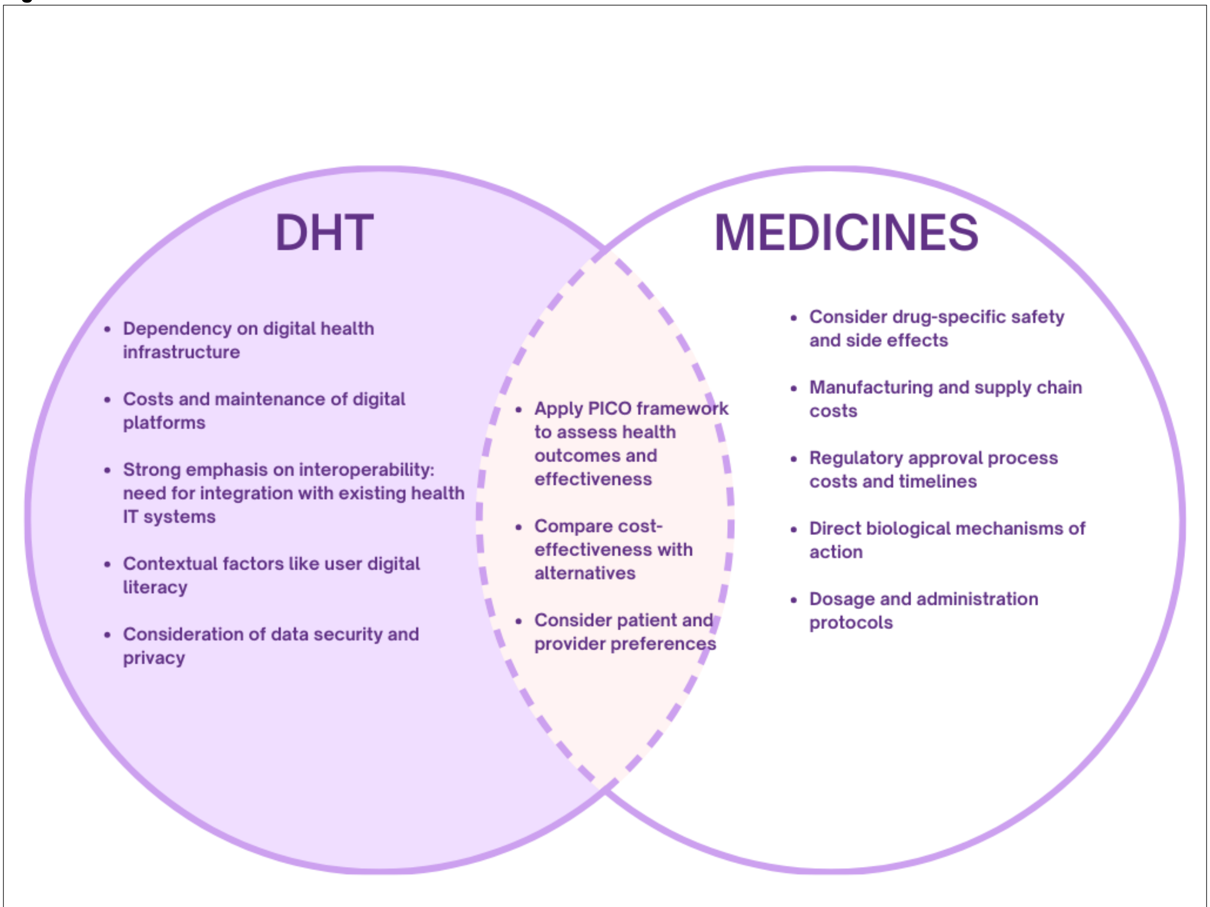
Unlike pharmacological assessments, digital health evaluation depends on the underlying infrastructure, both in terms of technology and in terms of human resources. This can be illustrated by evaluating not just a health app that monitors heart rate, but the entire digital infrastructure behind it, from cloud servers and interoperability standards to cybersecurity protocols, often without established models or precedents to guide implementation. This involves considerations that may be absent in traditional health technology assessment, such as data privacy concerns, ethical implications of algorithmic decision-making, societal attitudes toward AI, and regulatory ambiguities (Figure 2.1).

The development and testing of digital health interventions and medical devices often requires a co-design approach with intended users, and relies on timely, iterative feedback for technical upgrades and contextual adaptations. These dynamic factors limit the feasibility of conducting traditional randomised controlled trials (RCTs) to assess effectiveness and safety.

Economic evaluation of DHTs also requires careful consideration of potential harms and ethical concerns. These may include issues related to data privacy, algorithmic bias, unequal access, or unintended consequences from over-reliance on digital systems. While such harms are often difficult to quantify, their impact can be significant (Hanna et al. 2025). Frameworks for economic evaluation should, where possible, include qualitative and sensitivity analyses to explore the potential implications of these risks (Wilkinson et al. 2023). Integrating ethical dimensions, such as equity, autonomy, and informed consent, into broader health technology assessments can help ensure that evaluations reflect not only cost-effectiveness, but also societal values and acceptability (Assasi et al. 2016).

In addition, there is growing recognition of the need to incorporate environmental impact into health economic evaluations (Williams et al. 2024). Traditionally, such evaluations have focused primarily on costs and health outcomes. However, the healthcare sector is a significant contributor to carbon emissions and environmental degradation (Malik et al. 2021). As sustainability becomes a key priority for health systems globally, economic evaluations must evolve to reflect the broader societal costs and benefits of health interventions, including their environmental footprint. This is relevant for digital health and AI technologies in particular, which may reduce emissions through more efficient care delivery (e.g., telehealth reducing travel) but also contribute to energy consumption and e-waste (Crawford 2021).

Figure 2.1: Economic evaluation of DHTs versus medicines.



DTH= digital health technology; PICO=patient, intervention, comparator, outcome

The CCA framework is recommended for assessment of digital health interventions as it typically presents a broad range of costs and effects in a disaggregated manner (NICE 2022). This allows comparability of the results to the local context of the settings in which the decision is made. However, in the absence of unified measures of cost and benefits, decisions informed by the results of CCA rely on value judgments to decide whether additional spending can be justified by the health benefits it offers.

In practice, budget impact and return on investment analyses are often prioritised over traditional economic evaluations when determining the costs and potential savings associated with implementing digital health interventions. This is primarily because digital health initiatives frequently involve substantial upfront costs, such as infrastructure, software integration, and staff training, making immediate fiscal implications a key consideration. Additionally, long-term outcomes can be uncertain due to the rapid evolution of digital technologies, limiting the applicability of conventional cost-effectiveness measure (Woods et al. 2023).

Multi-criteria decision making

In many health system decisions, particularly those involving complex service or digital health interventions, decision makers must consider a broader set of objectives that extend beyond health gain alone. While conventional evaluations are essential for quantifying efficiency trade-offs, they may not fully capture the other benefits, such as user autonomy or system interoperability that define digital health maturity. In this context, multi-criteria decision making (MCDM) offers a structured framework to support decision making where multiple, potentially competing criteria are relevant.

The MCDM refers to a family of methods that explicitly incorporate multiple dimensions of value into a decision framework, extending evidence-based medicine and health technology assessment.

Within an economic evaluation context, MCDM is best understood as a complementary approach rather than a substitute for traditional economic evaluation. Economic evaluations remain essential for quantifying costs, cost offsets, and efficiency trade-offs. MCDM builds on this information by integrating economic evidence alongside other criteria that may be critical to adoption or scale-up decisions. For example, cost-effectiveness estimates can be included as one criterion within an MCDM framework, weighted alongside factors such as implementation risk, scalability, acceptability to users, or impacts on access and equity.

Multi-criteria decision analysis (MCDA) is a tool that helps decision-makers summarize complex value trade-offs in a way that is consistent and transparent. It is comprised of a set of techniques that bring about an ordering of alternative decisions from most to least preferred, where each technology is ranked based on the extent to which it creates value through achieving a set of policy objectives. In this context, multiple outcomes such as stakeholder preferences, clinical outcomes, implementation feasibility, patient experience, equity considerations, and strategic alignment can be simultaneously incorporated in decision making process. This is particularly relevant where interventions generate system-level or non-health benefits, such as those associated with digital health technologies, that may not readily be captured within conventional economic evaluation metrics (Marsh et al. 2017).

The use of MCDM is particularly advantageous in contexts where evidence is uncertain or heterogeneous, where outcomes are multidimensional, or where decisions must be made at an early stage of implementation. This has led to increasing interest in MCDM within health technology assessment and policy settings, especially for interventions such as digital health technologies, service redesigns, and models of care that challenge conventional evaluation paradigms.
Although MCDM is not a formally adopted framework in Australia, it can enhance decision making by systematically incorporating economic evidence within a broader value framework, supporting more informed and context-specific resource allocation decisions. However, application of MCDM may be challenging as there are many different MDCA methods. Results can be sensitive to the choice of criteria, scoring methods and weights, and there is potential for subjectivity. Stated preference methods, such as Discrete Choice Experiments (DCE) and Best-Worst Scaling (BWS), serve as a robust empirical framework for eliciting and quantifying preferences relevant to address these challenges. Stated preference methods provide a significant contribution to the broader evaluation frameworks, which can be integrated with traditional clinical and economic data to allow for a more balanced and context-sensitive interpretation of value. Integrating stated preference methods into the MCDM process enables a more comprehensive valuation of health technologies by aligning the assessment of value with the prioritised needs of the health system. In the context of digital health maturity, stated preference methods provide an empirical means of eliciting and quantifying stakeholder priorities, enabling maturity to be assessed in terms of capability, integration, and practical utility rather than nominal adoption or system readiness alone.

In conclusion, the evaluation of digital health interventions, consistent with health technology assessment more broadly, should be guided by a value-based approach. For digital health technologies, this extends beyond effectiveness and cost to include system readiness, interoperability, equity and access, long-term economic value and sustainability, and, critically, user-centred design and the evaluation of user preferences.

The following chapter builds on the concepts introduced in this chapter by presenting a scoping review of published economic evaluations of digital health interventions, using artificial intelligence–enabled technologies as an example, to examine how the evaluation frameworks are currently used in the literature. Subsequent chapters then introduce and apply stated preference methods (i.e. DCE and BWS) to capture stakeholder preferences.

Guidelines

The Professional Society for Health Economics and Outcome Research (ISPOR) has developed specialised guidelines specifically tailored to digital health and AI evaluation through its updated Consolidated Health Economic Evaluation Reporting Standards (CHEERS) statement to ensure that economic evaluations of AI-based health interventions are reported in a sufficiently transparent manner (Sagoo and Richardson 2024).Their guidelines establish methodological standards that ensure DHTs are evaluated with appropriate rigor within existing HTA frameworks while acknowledging their unique characteristics (Sagoo and Richardson 2024). This includes describing the details of the AI component, including how the effect of the AI is measured, how AI learning occurs over time, and how the AI component was developed and validated; reporting the results of analyses of uncertainty; and discussing the necessary requirements for implementation (Elvidge et al. 2024). By adhering to CHEERS-AI, researchers and evaluators can provide decision-makers with clearer insights into the value of AI-enabled health interventions, facilitating more informed policy and funding decisions. However, it is important to note that CHEERS-AI does not explicitly address issues related to data privacy and security, which are critical in the context of AI and digital health. While the guidelines focus on methodological transparency and reporting standards, the safe handling of patient data, adherence to privacy regulations, and potential ethical considerations in AI deployment are not systematically incorporated.

Building on the overview of existing economic evaluation frameworks, the following chapter presents a scoping review focused on the economic evaluation of AI in oncology. This review deepens the understanding of the unique challenges associated with assessing the value of DHTs, using application of AI in oncology as a representative case. Insights gained from this review have informed the design of the empirical studies presented later in this thesis (Chapters 5 and 6).

Chapter 3: Economic Evaluation of artificial intelligence in oncology: A scoping review of literature

The work presented in this chapter has been submitted for publication in Health Economics Review and is currently under review.

Publication manuscript details

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Abstract

Background: Artificial intelligence (AI) has significant potential to address pressing challenges in healthcare, particularly in improving access to, and quality, and efficiency of cancer care. AI technologies may streamline healthcare planning and delivery and reduce costs. An increasing number of AI-based applications are being developed and implemented across various cancers, including breast, colorectal, lung, and brain cancer, and in multiple domains such as diagnostics, immunotherapy, radiation therapy, and research. This scoping review aims to assess the current literature on health economic evaluations of AI in oncology, examine the methodological approaches used, and explore the potential economic benefits and risks associated with integrating AI into cancer care.

Methods: The literature on health economic evaluation (EE) of AI in oncology was reviewed from 1 January 2019 to April 2025. Papers were included if they included data on clinical effectiveness, resource utilisation, costs, and other relevant parameters related to AI systems in this field. The key information from the papers was extracted, including the author, year, country in which the study was conducted, study design, population, care pathway phase (e.g. diagnostic, planning, delivery).

Results: A total of 21 health economic evaluations were reviewed. Most studies focused on breast (n=5) and colorectal cancer (n=5) and were conducted primarily in Western developed countries, with 5 studies from Asia. No studies were identified from Africa, Latin America, the Middle East, or other regions. Cost-utility analysis was the predominant analytical approach, with Markov modelling being the most common methodology. The studies were conducted from a healthcare perspective and investigated AI use primarily in screening and diagnostics. The evaluations highlighted economic benefits associated with AI implementation due to improved accuracy, labour cost reduction, and improved workflow. Results contained uncertainties due to lack of established pricing for AI technologies, limitations in the quality of clinical evidence informing the models, and incomplete assessment of long-term and budget impacts.

Conclusions: Results suggest that AI has potential to be both cost-effective and cost-saving, particularly in screening and diagnostic phases of cancer care. However, there is uncertainty regarding the applicability of these results to real-world settings. Future research should explore the cost-effectiveness of AI across broader oncology settings and applications beyond screening and diagnosis. The predominance of model-based evaluations using cost-utility and cost-effectiveness frameworks indicates that AI interventions are largely being assessed within traditional health technology assessment paradigms. However, this approach often overlooks critical aspects unique to AI, such as algorithmic adaptability, data dependency, and lifecycle costs. This highlights the need for more tailored methodological frameworks that reflect the distinct characteristics and challenges of AI in healthcare.

Background

Artificial intelligence (AI) has emerged as a promising tool to address persistent challenges in healthcare, including increasing demand, workforce constraints, and the need for more efficient and personalised care. As AI applications continue to expand across clinical and operational domains, the evidence base describing their development, implementation, and impacts has grown rapidly and remains heterogeneous. To provide a structured overview of this evolving field, this chapter adopts a scoping review approach, which is well suited to mapping the breadth and nature of existing evidence, with focus on how AI is being evaluated, and to identify key knowledge gaps. The review is restricted to oncology, as cancer care, particularly radiotherapy, is data-intensive, complex, and protocol driven, making it a highly relevant domain for AI adoption. In addition, increasing incidence of cancer and capacity constraints underscores the strategic importance of oncology for AI-driven innovation.
Within this context, the scoping review aims to assess the current literature on health economic evaluations of AI in oncology, examine the methodological approaches used, and explore the potential economic benefits and risks associated with integrating AI into cancer care.

Introduction

AI has significant potential to address some of the most pressing challenges in healthcare, particularly in improving access to, and quality, and efficiency of care (Kumar 2025). It may streamline healthcare planning and delivery and reduce costs. An increasing number of AI-based technologies and applications are being developed and implemented across various cancer types, including breast, colorectal, lung, and brain cancer, and in multiple domains such as diagnostics, immunotherapy, radiation therapy, and research and development.

Despite these advances, concerns remain regarding the use of AI in healthcare. These include the risks of overdiagnosis, increased reliance on advanced and expensive diagnostic tests, deskilling of the labour force and uncertain long-term cost savings (Vithlani et al. 2023). The broader impact of AI on healthcare resource utilisation remains unclear, and healthcare institutions may incur substantial upfront costs, including those related to data acquisition, algorithm training, infrastructure upgrade, and regulatory compliance, before realising potential economic benefits.

In most publicly funded healthcare systems, health technology assessment (HTA) is required to evaluate clinical and cost effectiveness before a new technology can be adopted into clinical practice. While a growing body of evidence supports the accuracy and clinical efficacy of AI tools, there is still a notable gap in research on their cost effectiveness and broader implications for healthcare providers, patients, and system sustainability.

While a previous scoping review broadly examined the use of AI in healthcare (Vithlani et al. 2023). This review specifically focuses on economic evaluations of AI in oncology. This scoping review aims to assess the current literature on health economic evaluations of AI in oncology, examine the methodological approaches used, and explore the potential economic benefits and risks associated with integrating AI into cancer care. This targeted approach was undertaken to identify key gaps in the literature, inform future research and policy development in oncology, and better understand the challenges of conducting economic evaluation in this emerging field, given the complexity and rapidly evolving nature of AI technologies in healthcare.

Methods

The literature was reviewed to identify published peer-reviewed economic evaluations of AI-technology in oncology, based on the Preferred Reporting Items for Systematic reviews and Meta-Analysis extension for Scoping Reviews (PRISM-ScR) guidelines (Tricco et al. 2018). The search was conducted between 15 April 2025 and 29 April 2025 in PubMed, Scopus, and Google Scholar (first 10 pages) using a combination of search terms: ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Automation") AND ("Radiation Therapy" OR "Treatment Planning") AND ("Economic Evaluation" OR "Cost-effectiveness" OR "Cost-benefit" OR "Cost-utility") (Table A3.1, Appendix 3). The search terms and search strategy were informed by the previous scoping reviews of economic evaluations of AI in healthcare (Vithlani et al. 2023) and in oncology (Tun et al. 2024). Studies in English, that were published between 1 January 2019 to April 2025 were included. This period was chosen to capture the latest developments in the field of AI in oncology and the impact of COVID-19 pandemic on the acceleration of the use of AI in health (Hirani et al. 2024). Backward and forward citation searching was conducted to identify additional relevant studies beyond the initial database search. Eligible studies included peer reviewed research articles and reviews with focus on economic evaluations, i.e. cost-effectiveness analyses, cost-benefit analyses and cost-minimisation analyses. After initial screening, two independent reviewers (ML, KM) assessed the relevance of potentially eligible studies and appraised them according to predefined inclusion criteria to ensure that only studies directly addressing the economic impact of AI applications in oncology settings were included in the final analysis. Disagreements between reviewers were resolved through discussion, with a third reviewer consulted if consensus could not be reached.

Data extraction

After removing duplicates, studies were included if they met the following inclusion criteria: peer reviewed economic evaluation of AI-based interventions in oncology, including cost-effectiveness analyses, budget impact analyses in English. The full text of the included studies was reviewed to identify any potential exclusion criteria including study design (such as editorials, commentaries, or reviews without original data), population (studies involving non-human or non-oncology populations), intervention (those not involving AI applications), and language (non-English publications). Data were extracted for a range of relevant study characteristics, including the author, year, country in which the study was conducted, study design, population, care pathway phase (e.g. diagnostic, planning, delivery). Next, detailed information about the health economic evaluation including type of analysis and modelling techniques, time horizon, comparator, health and cost outcomes and perspective was extracted.

Data analysis

The extracted data were synthesised using a narrative approach as heterogeneity across the studies did not allow quantitative assessment. Descriptive statistics were used to summarise the characteristics of the included studies. Software for literature review, Zotero (Zotero 2025) and Rayyan AI (Rayyan 2025) were used to extract and analyse data.

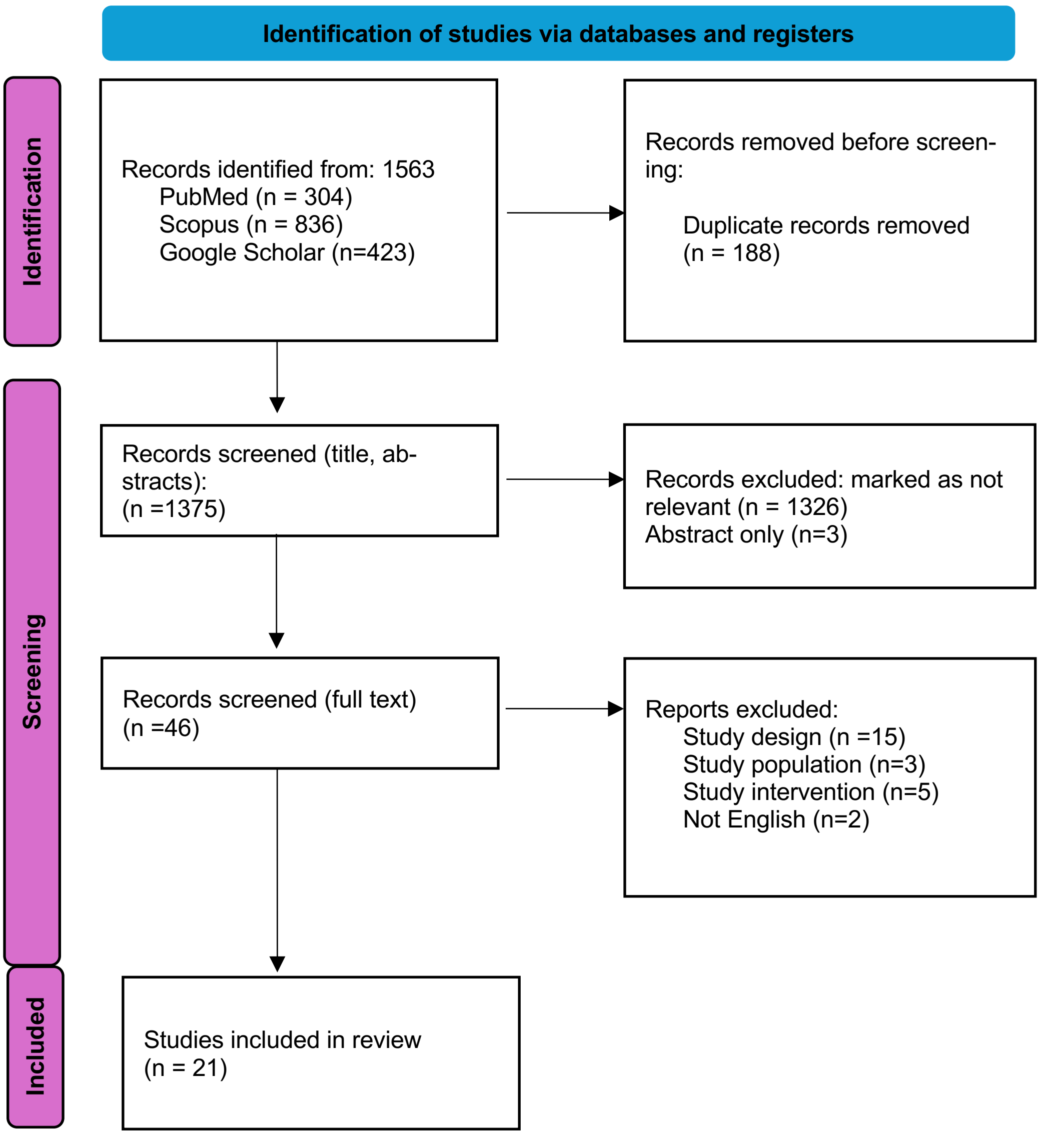
Quality assessment

The quality of the studies was assessed using Consolidated Health Economic Evaluation Reporting Standards (CHEERS) AI (Elvidge et al. 2024) and Philips checklist (Philips et al. 2004). CHEERS AI establish methodological standards that ensure digital health technologies (DHTs) are evaluated with appropriate rigor within existing HTA frameworks while acknowledging their unique characteristics (Sagoo and Richardson 2024). This includes describing the details of the AI component, including how the effect of the AI is measured, how AI learning occurs over time, and how the AI component was developed and validated; reporting the results of analyses of uncertainty; and discussing the necessary requirements for implementation (Sagoo and Richardson 2024). Each checklist item was assessed as fully reported (1 point), partially reported (0.5 points), or not reported (0 points), with non-applicable items excluded from calculation. A final score was calculated for all included studies based on the percentage of satisfied criteria across all 38 items (Elvidge et al. 2024). Publications were subsequently classified as high (≥80%), medium (50-79%), or low quality (<50%) based on their final scores, providing a standardised metric for evaluating reporting completeness and transparency in AI-based health economic evaluations (Elvidge et al. 2024). Philips checklist, which was specifically designed to evaluate the quality of model-based EEs, was used to assess modelling approach, model data, and uncertainty assessment in the included studies (Philips et al. 2004).

Results

Figure 3.1 presents the study selection process. A total of 1,563 records were identified. After removing duplicates and initial screening, 49 records were retained for further review. Subsequent screening excluded 28 records due to incorrect study design, intervention, or population characteristics, resulting in 21 studies included in the final analysis.

Figure 3.1: Study selection process



Overview of the studies

The characteristics of the included studies are presented in

Table **3.1**. The studies examined the economic implications of AI implementation across various cancer types: breast and colon were the most frequently studied (5 studies each, comprising 48% of the sample), followed by lung (2 studies, 10%), and colorectal and gastric cancers (with one study examining both types, representing 14% altogether). Skin, prostate, renal, and cervical cancers were each addressed in a single study (19% collectively). Additionally, two studies conducted economic reviews across diverse cancer types. Twenty studies primarily focused on the early stages of the care pathway, such as screening and diagnosis, while one study examined shared decision-making about treatment options. Regarding geographical distribution, 16 papers originated from Europe and North America, while Asia contributed 5 papers. No studies were identified from Africa, Latin America, the Middle East, or other regions, highlighting a significant gap in the global evidence base.

Table 3.1: Health economic methodology using Philips main item of included studies (N=21)

Author/Year/ Country	Title	Cancer type	Pathways stage	Population	Study design	CHEERS AI Score
Ahsen, 2025, USA	Economics of AI and human task sharing for decision making in screening mammography	Breast cancer	Screening	Women undergoing mammography screening;	Cost optimisation model	61%
Borsoi, 2024, Germany, Israel, Italy, Poland, Portugal	Artificial-Intelligence Cloud-Based Platform to Support Shared Decision-Making in the Locoregional Treatment of Breast Cancer: Protocol for a Multidimensional Evaluation Embedded in the CINDERELLA Clinical Trial	Breast cancer	Treatment (shared decision making)	Breast cancer patients undergoing locoregional treatment	Trial-based economic evaluation CUA Study protocol	76%
Hill, 2024, UK	Cost-Effectiveness of AI for Risk-Stratified Breast Cancer Screening	Breast cancer	Screening	UK women eligible for breast screening N=174,523	CUA	68%
Mital, 2022, USA	Cost-effectiveness of using artificial intelligence versus polygenic risk score to guide breast cancer screening	Breast cancer	Screening	Women aged 40 to 74 years	CUA	76%
Vargas, 2023, UK	Cost-effectiveness requirements for implementing artificial intelligence technology in the Women's UK Breast Cancer Screening service	Breast cancer	Screening	Cohort of 100,000 women age of 19 years and older	CUA	66%
Shen, 2023, China	Cost-effectiveness of artificial intelligence-assisted liquid-based cytology testing	Cervical	Screening	Unvaccinated and unscreened women aged 30–64 years	CUA	71%

Author/Year/ Country	Title	Cancer type	Pathways stage	Population	Study design	CHEERS AI Score
	for cervical cancer screening in China					
Adams, 2021, Canada	Development and Cost Analysis of a Lung Nodule Management Strategy Combining Artificial Intelligence and Lung-RADS for Baseline Lung Cancer Screening	Colon cancer	Screening	Individuals undergoing baseline lung cancer screening, with no specific age group mentioned	Simple cost comparison analysis	74%
Barkun, 2023, Canada	Cost-effectiveness of Artificial Intelligence-Aided Colonoscopy for Adenoma Detection in Colon Cancer Screening	Colon cancer	Screening	Canadian colorectal cancer screening programs and patients N=685	CUA	76%
Bustamante-Balén, 2025, Spain	Cost-effectiveness analysis of artificial intelligence-aided colonoscopy for adenoma detection and characterisation in Spain	Colon cancer	Screening	Colorectal cancer patients classified by stage in Spain	CUA	74%
Kacew, 2021, USA	Artificial Intelligence Can Cut Costs While Maintaining Accuracy in Colorectal Cancer Genotyping	Colon cancer	Diagnostic	Patients with colorectal cancer (data from SEER and other sources) N=32,549	CEA	66%
Mori, 2020, Japan	Cost savings in colonoscopy with artificial intelligence-aided polyp diagnosis: an add-on analysis of a clinical trial (with video)	Colon cancer	Diagnostic	Patients with diminutive rectosigmoid polyp (N=791)	Trial-based economic evaluation CMA	61%
Ariea, 2022, USA	Cost-effectiveness of artificial intelligence for screening colonoscopy: a modelling study	Colorectal	Screening	Hypothetical cohort of 100,000 individuals in the USA aged 50–100 years	CEA	68%
Libanio, 2024, Netherlands, Portugal, Italy	Combined gastric and colorectal cancer endoscopic screening may be cost-effective in Europe with the implementation of artificial intelligence: An economic evaluation	Gastric and colorectal	Screening	Men and women aged 50 to 75 years	CUA	68%
Yonazu, 2023, Japan	Cost-effectiveness analysis of the artificial intelligence diagnosis support system for early gastric cancers	Gastric cancer	Diagnostic	Patients with moderate to severe gastritis caused by Helicobacter pylori infection.	CUA	71%
Geng, 2025, China	A Cost-Effective Two-Step Approach for Multi-Cancer Early Detection in High-Risk Populations	General	Screening	Newly diagnosed cancer patients (n=617) and noncancer controls (n=580) from multiple hospitals in China	CEA	50%
Huang, 2025, China	The feasibility and cost-effectiveness of implementing mobile low-dose computed tomography with an AI-	General	Screening	Underserved rural populations in China	CEA	58%

Author/Year/ Country	Title	Cancer type	Pathways stage	Population	Study design	CHEERS AI Score
	based diagnostic system in underserved populations					
Ziegelmayer, 2022, USA	Cost-Effectiveness of Artificial Intelligence Support in Computed Tomography-Based Lung Cancer Screening	Lung cancer	Screening	Individuals undergoing lung cancer screening. The specific age group is not mentioned	CUA	63%
Trujillo, 2025, Spain	Cost-effectiveness of a machine learning risk prediction model (LungFlag) in the selection of high-risk individuals for non-small cell lung cancer screening in Spain	NSCL	Screening	individuals at-risk for enrollment in NSCLC screening programs,	CUA	68%
Gomez Rossi, 2022, USA	Cost-effectiveness of Artificial Intelligence as a Decision-Support System Applied to the Detection and Grading of Melanoma, Dental Caries, and Diabetic Retinopathy	Melanoma	Screening and diagnostic	General US population	CUA	71%
Du, 2024, Sweden	Effectiveness and Cost-effectiveness of Artificial Intelligence-assisted Pathology for Prostate Cancer Diagnosis in Sweden: A Microsimulation Study	Prostate	Screening	Men from the age of 50 years over a lifetime horizon, specifically aged 50–74 years for screening	CEA	66%
Marka, 2024, Germany	Artificial intelligence support in MR imaging of incidental renal masses: an early health technology assessment	Renal	Diagnostic	Patients undergoing nephrectomy or biopsy for renal tumors	CUA	78%

CEA = cost-effectiveness analysis; CMA = cost=minimisation analysis; CUA= cost-utility analysis;

Economic analysis

The 21 economic evaluations included 13 (61%) studies (Borsoi et al. 2024; Hill et al. 2024; Mital and Nguyen 2022; Vargas-Palacios et al. 2023; Shen et al. 2023; Barkun et al. 2023; Bustamante-Balén et al. 2025; Libanio et al. 2024; Yonazu et al. 2024; Ziegelmayer et al. 2022; Trujillo et al. 2025; Gomez Rossi et al. 2022; Marka et al. 2024) which were cost-utility analyses, with quality-adjusted life years (QALYs) as the primary outcome measure; 5 (23%) studies were cost-effectiveness analyses (CEA) with natural units of effectiveness (such as life-years gained or cases detected); and 3 studies which presented simple cost comparisons without incorporating health outcomes. One study (Borsoi et al. 2024) also included evaluation of patient satisfaction.

The cost effectiveness of AI in oncology was mostly assessed in the context of screening and diagnostics relative to current practice or no intervention. The AI technologies included AI technical subsystems such as machine learning, deep learning, and neural networks. In breast cancer, AI is integrated into mammography screening (Ahsen et al. 2025), risk-stratified screening strategies (Hill et al. 2024), and shared decision-making platforms (Borsoi et al. 2024), typically compared against expert-only approaches, national screening programs, or standard care. In cervical cancer, AI-assisted liquid-based cytology was evaluated against manual cytology (Shen et al. 2023) and HPV testing. For cardiopulmonary conditions, interventions include AI-supported computer tomography (CT) and low-dose CT (LDCT) for lung cancer, as well as risk prediction models and management tools, benchmarked against conventional imaging, Lung CT Reporting and Data System (RADS) (Adams et al. 2021), or population-based screening without AI. In gastrointestinal (GI) cancers, AI is incorporated into colonoscopy and endoscopy (e.g., computer-aided diagnosis (CADx) systems, GI Genius modules) (Bustamante-Balén et al. 2025), compared with standard procedures without AI assistance. In multi-cancer detection, two-step AI-enhanced approaches were tested against other emerging genomic screening tests (i.e. SeekInCare and Galleri) for individuals who tested positive in the initial screening (Geng et al. 2025). Lastly, in pathology and imaging, AI was used as a diagnostic-support tool or to augment MRI and pathology workflows, with comparisons made to human experts or MRI alone (Du et al. 2023). All the included studies compared conventional approaches with approaches that were integrated with AI. The studies that were CEAs or CUAs used decision tree and Markov modelling. The time horizon applied in the modelled evaluations varied from 1 year to a lifetime and was guided by the natural progression of the disease. The majority of studies adopted a healthcare system perspective for their economic analyses, while only 3 studies (Borsoi et al. 2024; Libanio et al. 2024; Areia et al. 2022) employed the broader societal perspective that incorporates indirect costs and benefits. Discounting was applied to costs and benefits in studies applying a time horizon beyond one year.

Modelling characteristics

Among the reviewed studies, three studies presented a basic costing assessment without accounting for clinical outcomes (Ahsen et al. 2025; Adams et al. 2021; Huang et al. 2025). Four types of economic modelling approaches were identified: Markov modelling (N=10); decision tree analysis (N=4); microsimulation (N=2), and discrete event simulation (DES) modelling (N=2). Modelling characteristics of these studies are summarised in Table 3.2. The choice of model type was based on claims about AI-intervention effectiveness, the outcome measure, and the time horizon. Among the studies that claimed AI-intervention superiority, the intervention was compared to other screening and diagnostic strategies (Mital and Nguyen 2022; Kacew et al. 2021; Mori et al. 2020; Ziegelmayer et al. 2022; Trujillo et al. 2025; Marka et al. 2024), no screening (Shen et al. 2023; Areia et al. 2022; Libanio et al. 2024; Huang et al. 2025), or the standard of practice (Barkun et al. 2023; Bustamante-Balén et al. 2025;

Yonazu et al. 2024; Gomez Rossi et al. 2022; Du et al. 2023; Vargas-Palacios et al. 2023; Hill et al. 2024; Borsoi et al. 2024). Most Markov models used a cycle length of 1 year (Mital and Nguyen 2022; Barkun et al. 2023; Bustamante-Balén et al. 2025; Areia et al. 2022; Libanio et al. 2024), and one study (Adams et al. 2021) used 6-month.

Table 3.2: Characteristics of the economic evaluation models in the included studies (N=21)

Author/ Year	Economic model/EHH type	Intervention	Comparator	Time horizon/cycle length	Perspective	Outcomes	Discount rate	SA	WTP threshold	Conclusions
Ahsen et al. 2025	Optimisation model to minimise mammography screening costs	Incorporating AI into mammography screening	Expert-alone strategy, automation strategy, delegation strategy	NA	Healthcare	Cost	NA	NR	NR	Cost savings of 17.5% to 30.1% compared to relying solely on human experts
Borsoi et al. 2024	Within-trial cost-consequence., CCA, CUA	AI cloud-based platform to support SDM in breast cancer patients undergoing locoregional treatment	Conventional approach to support SDM in breast cancer patients undergoing locoregional treatment	12 months after the end of locoregional treatment	Societal	QALYs (EQ-5D-5L), Patient satisfaction (5 point scale), Costs	NA	1-way and PSA	EUR50,000-10,000/QALY	NA: Study protocol.
Hill et al. 2024	CEA using DES and real-world data	AI-based risk-stratified breast cancer screening	Current UK National Breast Cancer Screening Program (screening every 3 years)	Lifetime	UK payer perspective	QALYs, Costs, Incremental	3.5%	1-way and PSA	GBP20,000/QALY	Risk-stratified screening was likely to be cost-effective, yielding added health benefits at reduced costs.
Mital et al. 2022	Decision tree and microsimulation, CEA	Combination of risk prediction approaches (AI, PRS or family history)	No screening, annual screening for all women,	Lifetime, 1-year cycles	Healthcare system	Cancer detection, Cost, QALYs	3%	1-way and PSA	USD100,000/ QALY	Risk prediction using AI followed by no breast cancer screening for low-risk women is the most cost-effective strategy.
Vargas et al. 2023	CEA, DES	AI-assisted mammogram	Standard practice	NA	Healthcare system	Cancer detection rate, Cost, QALYs	NA	1-way and PSA	GBP20,000/QALY	If non-inferiority is maintained, the use of artificial intelligence technology as a second reader is a viable and potentially cost-effective use of NHS resources.

Author/ Year	Economic model/EHH type	Intervention	Comparator	Time horizon/cycle length	Perspective	Outcomes	Discount rate	SA	WTP threshold	Conclusions
Shen et al. 2023	CEA, Markov model	AI-assisted liquid- based cytology	Manual LBC and HPV DNA testing	Lifetime	Healthcare provider	Cancer detection rate, Cost, QALY,	3%	1-way and PSA	USD30,000/QALY	AI-assisted LBC screening once every 5 years could be more cost-effective than manually read LBC.
Adams et al. 2021	Cost analysis: total cost estimation	AI informed management of atrial & Lung	Lung RADS only	6 months	Payer	Lung nodule classification, Cost	NA	NR	NR	Using an AI risk score combined with Lung-RADS at baseline lung cancer screening may result in fewer follow-up investigations and substantial cost savings.
Barkun et al. 2023	CEA, Markov model	Artificial intelligence-aided colonoscopy for adenoma detection	Conventional colonoscopy polyp detection	Lifetime horizon/ 1-year cycles	Canadian health care perspective	LYs, QALYs, Costs	3.5%	1-way and PSA	USD 50,000/QALY	CADe colonoscopy is cost-effective with cost savings of approximately $14 per case.
Bustamante-Balén et al. 2025	Markov model with, CUA	GI Genius Intelligent Endoscopy Module-assisted colonoscopy	Standard practice (colonoscopy alone)	Lifetime/1-year cycles	Spanish National Health System perspective	Life years gained (LYG), QALYs, Cost	3%	1-way and PSA	EUR25,000/QALY	CADe/CADx would result in a dominant strategy versus standard practice in patients undergoing colonoscopy in Spain.
Kacew et al. 2021	CEA, Decision Tree	8 next-generation sequencing (NGS) strategies[a]		1 year	US Healthcare	Clinical implications, time to treatment initiation, diagnostic accuracy, Costs,	NA	NR	NR	High-sensitivity artificial intelligence followed by confirmatory high-specificity polymerase chain reaction or immunohistochemistry panel for patients testing negative by artificial intelligence compared to next-generation sequencing alone in newly diagnosed metastatic colorectal cancer resulted in the greatest project cost savings ($400 million, 12.9%)

Author/ Year	Economic model/EHH type	Intervention	Comparator	Time horizon/cycle length	Perspective	Outcomes	Discount rate	SA	WTP threshold	Conclusions
Mori et al. 2020	EE along clinical trial, CMA	AI combined with a diagnose-and-leave strategy;	no use of AI, resect-all-polyps strategy	NA	Healthcare system	Polyps detection and pathologic prediction, Cost	NA	NR	NR	The use of AI to enable the diagnose-and-leave strategy results in substantial cost reductions for colonoscopy.
Areia et al. 2022	Markov Model, CEA	AI assisted colonoscopy for polyps detection	Colonoscopy without the use of AI for polyp detection.	5 years, 1 year cycles	Societal	Number of colorectal cancer cases and colorectal cancer-related deaths, Costs	3%	1-way and PSA	NR	AI detection tools in screening colonoscopy is a cost saving ($57 per patient) strategy to further prevent colorectal cancer incidence and mortality.
Libanio et al. 2024	Markov model, CEA	AI assisted EDG	Stand alone EDG	NR/ 1 year cycles	Societal	Disease progression, Cost, QALYs	3%	1-way and PSA	EUR46,000-80,000/QALY	AI-assisted EGD may improve the cost-effectiveness of GC screening with combined EGD and screening colonoscopy. The actual effect of AI on cost-effectiveness may vary dependent on the accuracy and costs of the AI system.
Yonazu et al. 2024	Decision trees with Markov models, CUA	Computer-assisted diagnosis (CADx) system for early gastric cancers and Endoscopist	Pre-artificial intelligence status quo: Endoscopist alone	3 years	Payers perspective	Disease progression, Cost, QALYs	2%	1-way and PSA	USD50,000/QALY	Using CADx for EGCs may decrease their misdiagnosis, contributing to improved cost-effectiveness in Japan.
Geng et al. 2025	Simulation analysis using two-step	Two-step MCED approach using OncoSeek	SeekInCare and Galleri	NA	Healthcare system perspective	Number of cancer cases detected,	NA	NR	NR	The two-step approach significantly reduces false positives and screening costs, making it a cost-

Author/ Year	Economic model/EHH type	Intervention	Comparator	Time horizon/cycle length	Perspective	Outcomes	Discount rate	SA	WTP threshold	Conclusions
	MCED approach, CEA	and SeekIn-Care				number of false positives, Costs				effective strategy for population-wide cancer screening.
Huang et al. 2025	Feasibility analysis, CEA	Mobile low-dose computed tomography (LDCT) with AI-based diagnostic system	NA	NA	Healthcare system	Lung cancer detection rate, Costs	NA	NR	NR	The LDCT with AI model for lung cancer screening holds economic promise for reducing health disparities in underserved areas and promoting larger populations in similar low-income countries.
Ziegelmayer et al. 2022	Markov model, CEA	CT augmented by AI	Conventional CT	20 years	Healthcare	Cost, QALYs	3%	1-way and PSA	USD100,000/ QALY	CT + AI resulted in a negative incremental cost-effectiveness ratio (ICER) as compared to CT only, showing lower costs and higher effectiveness.
Trujillo et al. 2025	Decision tree with Markov model CUA	Lung Flag risk prediction model	screening the entire target population meeting USPSTF criteria with LDCT without using any RPM (screening without RPM) Non-screening (current)	Lifetime	Healthcare	Cancer progression QALYs LY	3%	1-way and PSA	EUR20,000-30,000/QALY	Using LungFlag for the selection of high-risk individuals for NSCLC screening in Spain would be a cost-effective strategy over screening the entire population meeting USPSTF 2013 criteria and is dominant over non-screening
Gomez Rossi et al. 2022	Markov models, CEA	AI as a diagnostic-support system	Standard of care	Lifetime	Payer perspective	Costs, QALYs,	3%	1-way and multivariate	USD18,496/QALY	AI showed mean costs of $750 (95% CI, $608-$970) and was associated with 86.5 QALYs (95% CI, 84.9-87.9 QALYs), while the control showed higher costs $759

Author/ Year	Economic model/EHH type	Intervention	Comparator	Time hori-zon/cycle length	Perspec-tive	Out-comes	Dis-count rate	SA	WTP thresh-old	Conclusions
										(95% CI, $618-$970) with similar QALY outcome.
Du et al. 2023	Microsimula-tion study, CEA	AI-assisted pathology	Human pathologist	1 year	Health care	CT scan reading time Cost	3%	NR	NR	Given current pricing, DL-CAD must be priced substantially below €6 in a pay-per-case setting or used in a high-workload environ-ment to reach break-even in lung cancer screening. DL-CAD as pre-screening reader shows the larg-est potential to be cost-saving.
Marka et al. 2024	Decision tree model CUA	MRI + AI strat-egy	MRI strategy alone	10 years	Healthcare sector per-spective	QALYs, Costs	3%	1-way and PSA	USD100,000/ QALY	The integration of an AI-based al-gorithm may be a potentially cost-effective alternative in the differen-tiation of incidental renal lesions using MRI.

CCA = Cost-Consequence Analysis; CEA = Cost-Effectiveness Analysis; CI = Confidence Interval; CT = Computed Tomography; CUA = Cost-Utility Analysis; DES = Discrete Event Simula-tion; DL-CAD = Deep Learning–Based Computer-Aided Detection; EQ-5D-5L = EuroQol 5-Dimension 5-Level; EUR = Euro; HPV DNA = Human Papillomavirus Deoxyribonucleic Acid; LBC = Liquid-Based Cytology; Lung-RADS = Lung Imaging Reporting and Data System; LYG = Life Years Gained; MRI = Magnetic Resonance Imaging; NGS = Next-Generation Sequencing; NR = Not Reported; PSA = Prostate-Specific Antigen; QALY = Quality-Adjusted Life Year; SA = Sensitivity Analysis; USD = United States Dollar

Note: a. NGS alone, high-sensitivity PCR or IHC panel ("panel" for short) alone, high-specificity panel alone, high specificity AI alone, high-sensitivity AI with confirmatory NGS for patients testing negative by AI, high-specificity AI with confirmatory NGS for patients testing positive by AI, high sensitivity AI with confirmatory high-sensitivity panel for patients testing positive by AI, and high-sensitivity AI with confirmatory high-specificity panel for patients testing positive by AI

Model inputs: efficacy estimates

Among the CEAs the efficacy outcomes included QALYs and survival (Borsoi et al. 2024; Hill et al. 2024; Mital and Nguyen 2022; Vargas-Palacios et al. 2023; Shen et al. 2023; Barkun et al. 2023; Bustamante-Balén et al. 2025; Libanio et al. 2024; Yonazu et al. 2024; Ziegelmayer et al. 2022; Trujillo et al. 2025; Gomez Rossi et al. 2022; Marka et al. 2024), number of cancer cases detected (Mital and Nguyen 2022; Vargas-Palacios et al. 2023; Shen et al. 2023; Mori et al. 2020; Areia et al. 2022; Geng et al. 2025; Huang et al. 2025), cancer progression (Trujillo et al. 2025; Yonazu et al. 2024; Libanio et al. 2024). Most evaluations relied on previously published literature, with only a few utilising high-quality primary evidence (e.g. RCT). Borsoi et al. (2024) was a study protocol that investigated outcomes directly from the CINDERELLA trial (prospective multicentre randomised controlled trial (RCT) (ClinicalTrials.gov: NCT05196269). Barkun et al. (2023) and Areia et al. (2022) based their estimates of clinical efficacy on RCT data, with the latter specifically using a meta-analysis of five trials. The majority of studies (Hill et al. 2024; Mital and Nguyen 2022; Geng et al. 2025; Ziegelmayer et al. 2022; Shen et al. 2023; Bustamante-Balén et al. 2025; Kacew et al. 2021; Libanio et al. 2024), sourced their efficacy estimates from existing published literature and systematic reviews. Some studies relied on less robust evidence sources, such as Trujillo et al. 2025 who used case-control studies and expert opinion, and Gomes Rossi et al. 2022 who utilised comparative accuracy studies. Marka et al. 2024 based their parameters on a multicentre cohort study, while Yonazu et al. (2024) reconstructed efficacy data from published reports and health registries. Du et al. 2023 used a mixed approach, sourcing data from literature for current strategies while making assumptions for AI-based interventions.

Model inputs: utility estimates

Studies that used CUA derived utility values from various sources, with most studies utilising established generic health-related quality of life instruments. Four studies (Borsoi et al. 2024; Bustamante-Balén et al. 2025; Ziegelmayer et al. 2022; Marka et al. 2024) employed the EQ-5D-5L (EUROQOL 2025) Two studies (Ziegelmayer et al. 2022; Marka et al. 2024) used the SF-36 instrument in addition to EQ-5D-5L (Ware and Gandek 1998). Several other evaluations (Mital and Nguyen 2022; Vargas-Palacios et al. 2023; Shen et al. 2023; Barkun et al. 2023; Trujillo et al. 2025) sourced utility values from previously published economic evaluations. Borsoi et al. (2024) uniquely incorporated disease-specific patient-reported outcomes through the BREAST-Q tool from the International Consortium for Health Outcomes Measurement (ICHOM), focusing specifically on patient satisfaction with breast cancer treatment measured on a four-point scale and converted to a 0-100 synthetic score. Yonazu et al. 2024 employed a direct preference elicitation approach using the standard gamble (SG) instrument (Gafni 1994) in patients to determine utility weights across various gastric cancer stages and treatment strategies, while also drawing from previously published economic evaluations. The quality-of-life estimates in Marka et al. (2024) came from retrospective telephone assessments using SF-36 and published systematic literature reviews. Notably, several studies (Gomez Rossi et al. 2022; Libanio et al. 2024; Hill et al. 2024) did not clearly specify their sources for utility estimation, representing a methodological gap in these evaluations.

Assessment of AI Implementation in clinical settings

Among the reviewed studies, the protocol by Borsoi et al. (2024) uniquely addressed comprehensive implementation aspects of AI in clinical settings, proposing to evaluate usability, acceptability, organisational impact, feasibility, and environmental consequences of the CINDERELLA mobile application for breast cancer treatment decision-making.

For usability assessment, the protocol describes employing validated instruments including the mHealth Apps Usability Questionnaire (MAUQ) for patients, which evaluates three dimensions (ease of use, interface satisfaction, and usefulness) across 18 items on a seven-point scale. Additionally, they plan to incorporate the user version of the Mobile App Rating Scale (uMARS), focusing specifically on the four-question information quality subscale rated on a five-point scale.

The protocol outlines how to measure acceptability from patients and healthcare professionals' perspective through app usage statistics, MAUQ questionnaire responses, semi-structured interviews, and focus groups. The organisational impact evaluation was designed to utilise focus groups to examine changes in work processes, human resource requirements, professional relationships, resource needs, and patient involvement following AI implementation.

The proposed feasibility assessment integrates findings from economic evaluation, usability, acceptability, and organisational impact analyses. This protocol also incorporates environmental impact assessment based on the quantity of services used, appropriateness of care delivery, and emissions associated with healthcare provision. This included quantification of healthcare service utilisation, travel distances to healthcare facilities, and transportation modes.

Resource utilisation

The studies incorporated various cost categories, with most studies including direct healthcare costs such as hospitalisations and health services (diagnostic procedures, treatments, and surgeries).

Several studies (Borsoi et al. 2024; Libanio et al. 2024; Areia et al. 2022) also included indirect costs such as productivity losses, and informal care.

The pricing approaches for AI technologies varied across studies: Trulijo et al. (2025) modelled the cost of LungFlag using an annual license fee structure, estimating approximately €60,000 annually for the 17 licenses required for implementation across Spain. Du et al. (2023) and Areia et al. (2022) employed a more detailed approach, evaluating multiple AI pricing models offered by system providers (including pay-per-use, one-off perpetual licensing, and yearly subscriptions) and incorporating estimated labour costs based on radiologist hourly rates. This variability in cost modelling approaches reflects the evolving economic frameworks surrounding AI implementation in cancer care settings.

Reported results

The results in most studies were reported as incremental cost effectiveness ratio (ICER) (i.e. the difference in total mean costs between the intervention and comparator divided by the differences in effectiveness (QALYs or natural units)) (Barkun et al. 2023; Borsoi et al. 2024; Bustamante-Balén et al. 2025; Hill et al. 2024; Gomez Rossi et al. 2022; Libanio et al. 2024; Marka et al. 2024; Mital and Nguyen 2022; Shen et al. 2023; Trujillo et al. 2025; Vargas-Palacios et al. 2023; Yonazu et al. 2024; Ziegelmayer et al. 2022) cost saved per patient screened/cost per case prevented (Areia et al. 2022; Du et al. 2023; Geng et al. 2025; Huang et al. 2025) and cost savings (Adams et al. 2021; Ahsen et al. 2025; Kacew et al. 2021; Areia et al. 2022). In addition, one study (Hill et al. 2024) reported incremental net monetary benefit (INMB) and one study reported the results in terms of break-even analysis, while three studies presented the overall costs associated with the use of AI (Ahsen et al. 2025; Adams et al. 2021; Huang et al. 2025). Thirteen (62%) EEs (Borsoi et al. 2024; Hill et al. 2024; Mital and Nguyen 2022; Vargas-Palacios et al. 2023; Shen et al. 2023; Barkun et al. 2023; Bustamante-Balén et al. 2025; Libanio et al. 2024; Yonazu et al. 2024; Ziegelmayer et al. 2022; Trujillo et al. 2025; Gomez Rossi et al. 2022; Marka et al. 2024) reported the AI intervention was cost effective versus the comparator relative to an explicit or implicit threshold value (see Table 3.2). In 6 (29%) studies (Ahsen et al. 2025; Barkun et al. 2023; Adams et al. 2021; Kacew et al. 2021; Du et al. 2023; Mori et al. 2020) the AI interventions produced potential cost savings. Adams et al. (2021) noted that demonstrated cost savings were primarily attributable to increased specificity afforded by AI algorithms and subsequent reduction in unnecessary follow-up investigations.

Two studies (Shen et al. 2023; Huang et al. 2025) noted particular challenges with how AI systems would be incorporated into clinical practice and the impact of contextual and individual factors affecting adoption, for example existing technology infrastructure and qualified personnel in underserved rural areas. The results from Shen et al. (2023) demonstrated that cost-effectiveness thresholds depend heavily on factors such as radiologist salaries and workload volumes, with AI systems becoming more economically viable in high-volume settings or when professional costs are higher. The findings suggest that AI-implementation strategy based on combined human-machine workflows may be most effective when designed to complement rather than replace human expertise. This approach achieved cost reductions between 17.5% and 31.1% (Ahsen et al. 2025).

Fourteen studies presented sensitivity analyses (14/21, 67%), mostly using deterministic and probabilistic sensitivity analyses. The results of sensitivity analyses showed that economic evaluation outcomes were sensitive to changes in the estimates informing AI accuracy and costs. Subgroup analyses were planned and have not been reported yet, in one study (Borsoi et al. 2024) to investigate how costs and outcomes vary between different patient subgroups, based on factors such as age, education level, marital status, comorbidity profile, employment status, digital health literacy, and trial country.

Quality assessment

The CHEERS-AI and Philips checklist was used to assess the methodological quality of the studies (Table A3.2 and Table A3.3, Appendix 3). The scores ranged from 50% to 78%, with an average of 68%, as indicated in Table A3.2, Appendix 3. The study that received the highest score used a decision tree model to examine the cost-effectiveness of MRI with artificial intelligence compared to conventional MRI, in distinguishing whether incidentally found renal lesions were benign or malignant (Marka et al. 2024). Although most studies provided explicit statements on the checklist, none involved an approach to patient participation and engagement. Regarding the AI-related items specifically, all studies indicated whether the AI intervention was directive or whether users would retain autonomy to make care decisions. Although the description of the AI components and validation of performance estimates was presented in six studies, the impact of AI uncertainty on the cost-effectiveness was discussed in only one study (Ahsen et al. 2025). Four studies (19%) state that the model's learning performance will be impacted over time by the assumptions made during model development, such as assuming data used in deployment will resemble the data used during training and key feature and outcome definitions don't change, which may not hold in real-world settings (Areia et al. 2022; Shen et al. 2023; Ziegelmayer et al. 2022; Adams et al. 2021). Five studies discussed requirements needed to integrate the AI intervention (and comparators, as appropriate) into practice, and other implementation considerations relating to the AI component of the intervention, including implications for the interpretation of cost-effectiveness results. Additional information regarding the CHEERs-AI checklist can be found in Table A3.2, Appendix 3.

Discussion

This review reports results that build on the review conducted by Tun 2024 (Tun et al. 2024), including an updated search of literature. Tun et al provided an overview of the EE evidence base for AI health technologies in oncology, and identified 12 studies, 9 of which were also included in this review. The remaining three studies were excluded due to an incorrect intervention (Thiruvengadam et al. 2023), incorrect design (Reason et al. 2024) or limited information (abstract only) (Kenseth et al. 2024).
This review demonstrates economic evaluations of AI health interventions in oncology, were reported as cost-effective or dominant compared to conventional approaches. However, important methodological and reporting limitations persist.

A total 21 EE were identified, primarily assessing AI-based automated image analysis interventions for diagnosis and screening in oncology. Nearly all were CUAs and CEAs. Some of the EEs only presented trial-based analyses, but the large majority were model-based and mostly used Markov models presenting results beyond the trial period. All the included studies compared conventional approaches with AI integration in oncology showing that hat AI improved outcomes and/or lowered costs and improved cost-effectiveness. Most studies adopted healthcare system or payer perspectives with lifetime horizons, following established EE methodological approaches (Drummond et al. 2015). In terms of the EE results, the AI interventions were found to be cost effective or dominant in 13 studies and potentially cost saving in six studies. The remaining two studies did not report cost-effectiveness, because one was a protocol (Borsoi et al. 2024) and the other was not a full economic evaluation (Huang et al. 2025).

This scoping review reveals that the benefits for AI use is particularly useful in supporting screening and diagnosis. The predominance of model-based evaluations using cost-utility and cost-effectiveness analysis frameworks suggests AI interventions are being increasingly evaluated within traditional health technology assessment (HTA) paradigms. However, Markov models and decision trees may not adequately capture the dynamic nature of AI technologies. Unlike traditional medical interventions, AI systems can potentially improve over time as they learn from additional data, challenging standard assumptions about fixed intervention effects (Adekunle 2024; Hendrix et al. 2022). Simulation-based modelling approaches present opportunities to build more flexible models capable of addressing the dynamic nature of AI interventions and capturing complex downstream effects in clinical pathways. However, microsimulation inherently incorporates considerable uncertainties due to calculation assumptions. Sensitivity analyses consistently revealed that results were highly dependent on AI accuracy parameters and implementation costs.

Most studies sourced the model inputs from published literature focused on prediction accuracy and precision rather than clinical effectiveness. There is a notable lack of RCTs directly comparing AI with current practice, with most studies relying on published data supplemented by multiple assumptions regarding compliance, time horizons, and model inputs, potentially yielding overestimated results. Data on efficacy of AI was obtained from different studies and demographic and personal risk factors considered in the analyses. The differences in healthcare characteristics, clinical practices, and service accessibility across different settings, may limit the generalisability of the study results. Two studies (Adams et al. 2021; Kacew et al. 2021) acknowledged that datasets used for AI training may not be representative of diverse target populations, particularly racial minorities. This raises important questions about equitable benefit distribution across demographic groups. This pattern highlights a critical need for more primary effectiveness research specific to AI applications in cancer care to strengthen future economic evaluations.

Most evaluations adopted healthcare or payer perspectives, omitting patient-incurred costs that would be included in societal perspectives. Studies varied in their approach to AI technology pricing models, with some considering licence-based approaches and others using pay-per-analysis models. Cost of using AI in clinical practice was often based on assumption as it was not yet known and was not available from the existing literature. Given the current financial pressures on healthcare systems, however, a high set-up cost or annual maintenance of AI systems could be a barrier to implementation.

AI implementation success depends on broader socio-technical and economic factors that transcend the technology itself. The results of this review show that AI effectiveness is contingent upon contextual integration factors rather than algorithmic performance alone. The challenges identified in rural settings (Huang et al. 2025) illustrate how infrastructure limitations and resource constraints can undermine even technically sound AI solutions. AI systems were shown to be more viable when professional resource costs are high or when deployed at scale. The studies noted the importance of the upstream process quality and human capability development. The optimal AI deployment followed a complementary rather than substitutive model, where technology augments human capabilities within carefully designed workflows. These findings collectively indicate that AI implementation success requires systems thinking that addresses organisational, economic, and human factors alongside technical considerations. Quality assessment of the included studies showed that most studies had limitations arising from data sources and input assumptions. This aligns with previous findings suggesting that despite increasingly sophisticated economic evaluation techniques, the underlying evidence remains limited (Vithlani et al. 2023).

None of the included studies were conducted for the Australian healthcare setting. There was a notable lack of studies exploring different care settings, particularly rural areas and middle-income countries, despite AI technologies' potential to address healthcare personnel shortages and overcome barriers to advanced medical equipment access in these settings. This gap is significant, as highlighted by Huang who noted the challenges with implementation and scaling up of AI-assisted programs in underserved rural areas that face insufficient human resources and logistical constraints. The "digital divide" remains a significant barrier, as unequal access to digital infrastructure hampers effective AI implementation globally.

The studies were focused on screening and diagnosis applications, with no studies evaluating AI across other phases of cancer treatment. This represents a significant gap in understanding the comprehensive value proposition of AI across the entire oncology care continuum. However, there are AI applications emerging across the broader oncology care continuum, including treatment planning, monitoring, and survivorship, which are not yet captured in existing evaluations. This points to an important gap in understanding the full economic and clinical value of AI in cancer care.

A key strength of this scoping review is the application of the CHEERS-AI checklist to assess the quality of included economic evaluations of AI-based health technologies. The CHEERS-AI checklist is a recently developed extension of the Consolidated Health Economic Evaluation Reporting Standards (CHEERS) (Elvidge et al. 2024), specifically designed to guide and improve the reporting of economic evaluations involving AI interventions. Its use is particularly important given the unique methodological and implementation challenges associated with AI in healthcare, including issues related to transparency, model adaptability, and integration into clinical workflows.

Potential future research directions

To advance the research in this field, the following future research areas are of interest:

- Collection and analysis of real-world evidence following implementation to clarify how improvements in diagnostic accuracy impact cost-effectiveness;
- Consideration of expected value of information analysis to assess parameter uncertainty and guide research and development priorities;
- Expansion of studies to include broader oncology settings and applications beyond screening and diagnosis.

Addressing these recommendations would significantly strengthen the evidence base and promote more informed decision-making regarding the economic value of AI interventions in oncology care.
Overall, the findings of this scoping review reinforce the limitations of applying traditional economic evaluation approaches to DHTs, as discussed in Chapter 2 of this thesis. In particular there remains a narrow focus on health outcomes and reliance on QALYs, which often fail to capture the broader value these technologies can offer, such as increased patient empowerment (Bracey et al. 2025), improved healthcare system efficiency (Faiyazuddin et al. 2025) , reduced healthcare resource use through remote monitoring (Ramezani et al. 2025; Mohanadas 2025), enhanced communication (Clay et al. 2024), and productivity gains (Olawade et al. 2024). Most of the studies included in this review evaluated only health-related benefits, overlooking the wider social, behavioural, and system-level impacts. This highlights the need for methodological adaptations to better reflect their unique and multifaceted value. For example, further research may consider the use of stated preference (SP) methods, which provide a robust framework for assessing the value of DTHs such as AI, by addressing their multifaceted impacts.
This scoping review has several limitations that should be considered when interpreting the findings. First, the search strategy was deliberately focused on identifying economic evaluations of AI in oncology, which may have limited the capture of studies using broader economic or decision-analytic frameworks, such as health technology assessment, or multi-criteria decision analysis. While this targeted approach aligned with the primary review objective, it may have resulted in the under-representation of relevant studies that evaluated AI using alternative or complementary assessment methods. Finally, the limited number of studies identified highlights the evolving nature of the field and suggests that relevant evidence may exist outside the scope of the current search or in grey literature not captured by the databases searched.

Chapter 4: Preference research methodologies

The preceding chapter presented the findings of a scoping review examining the current landscape of economic evaluations of artificial intelligence (AI) in oncology. The review revealed a growing body of literature in this area, with evidence suggesting that AI can be both cost-effective and cost-saving, particularly in the screening and diagnostic phases of cancer care. However, it also highlighted key limitations, notably the uncertainty around the real-world applicability of these results and the narrow focus on model-based evaluations using traditional cost-utility and cost-effectiveness frameworks. These approaches often fail to capture unique features of AI technologies, such as algorithmic adaptability, data dependency, and evolving lifecycle costs. Together, these findings point to a need for more flexible and context-sensitive methods to assess the value of AI and other digital health interventions.

Considering these evidence gaps, this chapter introduces stated preference (SP) methods as a promising approach to complement existing evaluation frameworks. These methods offer a way to capture stakeholder preferences, providing insights into the perceived benefits and trade-offs associated with digital health innovations such as AI. The empirical analyses presented in this thesis will build on these methods, applying them to investigate how different stakeholders value digital health technologies.

Stated preference methods, such as discrete choice experiments, are particularly suited for assessing digital health interventions because they allow the elicitation of preferences for specific features, trade-offs, and outcomes that may not yet be observable in real-world usage. Unlike revealed preference approaches, which rely on actual behaviour or uptake data, stated preference methods can capture hypothetical or future scenarios, enabling the assessment of innovations, emerging technologies, or complex interventions where market data are limited or unavailable. This makes SP methods especially valuable for evaluating digital health solutions, where adoption, usability, and perceived benefits vary across users and contexts (Mühlbacher and Johnson 2016).

Stated preference methods are applied in this thesis to explore various aspects of the value attributed to improvements in digital health maturity and their implications for users and the overall system. This analysis is conducted using two case studies, each showcasing significant recent advancements in DHTs expected to revolutionise the healthcare sector, specifically the application of artificial intelligence (AI) technology in radiation oncology and the evaluation of the Australian National Digital Health Strategy (NDHS). The studies are based on a structured approach, incorporating SP methods, including BWS and DCEs. The following sections of this chapter provide an overview of the choice experiment methodology, including survey development, statistical design, and data analysis. In the subsequent chapters, this methodology is applied to explore the adoption of AI in radiation therapy and the evaluation of the NDHS.

Choice-based preference measurement methods

Understanding value is essential for informing priority setting and decision-making, particularly in healthcare. This process is guided by the preferences of consumers as well as other key decision makers, such as providers and policy makers. In economics revealed preference is inferred from choices made in markets, under circumstances where there is no market failure. However, due to distinctive features of health and healthcare goods (e.g., uncertainty, risk, quality of life) which are typically not traded in conventional markets, estimating consumer preferences using revealed preference data can be challenging. Hence, stated preference methods have become widely used.

Stated preference methods are used to understand individual's priorities, using surveys in which respondents choose from a set of predefined options. A key component of these surveys is that the choice tasks are clearly defined and systematically constructed as part of designed experiment, enabling valid estimation of the underlying preference model (Mühlbacher and Johnson 2016). Choice-based preference measurement methods are grounded in Random Utility Theory, a well-established framework in human decision-making proposed by Thurstone and generalised by McFadden (Flynn et al. 2007). Methods such as discrete choice experiments (DCEs) and best-worst scaling (BWS) are tools that can be used to inform value frameworks for digital health technologies (DHTs). They allow quantitative assessment of a wide range of criteria relevant for the assessment of DHTs, such as clinical effectiveness, cost-effectiveness, patient experience, usability, equity, and data security. By systematically capturing how different stakeholders, including patients, clinicians, and payers, prioritise various attributes of DHTs, SP methods reveal the trade-offs users are willing to make (e.g., between data privacy and real-time feedback). These insights provide input into multi-criteria decision analyses, economic evaluations, and help shape the design, implementation, and reimbursement of DHTs.

Choice-based experiments

Choice-based experiments are a family of methods used to study decisions people make when faced with alternative options. By systematically varying the characteristics of these options and observing the choices individuals make, researchers can study preferences and trade-offs. Within this family of methods, DCEs and BWS are two of the most frequently applied approaches, each offering distinct ways to capture and analyse preferences. The following sections provides the conceptual foundation and background necessary for the subsequent empirical chapters, which apply the DCEs (Chapters 5 and 6) and BWS (Chapter 7) approaches.

Discrete choice experiment (DCE)

A DCE is a type of SP method used to understand people's preferences by asking them to make choices between alternative options, often called profiles. In this situation respondents evaluate profiles that consist of multiple attributes, with each attribute taking on a specific level from a finite set of possible levels. The attributes may be either quantitative or qualitative and their levels are selected from a plausible and policy-relevant range (Street and Viney 2019) to reflect a subset of the possibilities that respondents may face. A combination of sources should be used to inform the identification and development of the attributes and their corresponding levels. These sources could include published literature, stakeholder consultations, and qualitative research focused on the population of interest. The purpose of the literature review is twofold: to identify whether any previous research has been undertaken on the topic (or a closely related topic) or, if not, whether there is any (and if so, sufficient) qualitative research available to inform the development of suitable items (that is, the master list) for the survey. If a number of published papers report similar findings, the need for expert guidance is reduced and preliminary qualitative research is not required. Selecting attributes with minimal correlation improves statistical efficiency, reduces the need to address multicollinearity in the analysis, and provides clearer insights into respondent preferences. While there is no specific written guideline regarding the number of attributes a DCE should include, prior studies have shown that an increase in the number of attributes leads to a situation where the cognitive burden stemming from increased volume of information will increase complexity-induced choice inconsistency (DeShazo and Fermo 2002).

Attribute levels are assigned to an attribute as a part of the designed experiment development. The multiple levels of each attribute are then varied systematically across the options in the choice tasks, and the respondents are asked to choose the option they prefer from each choice task they are shown in Figure 4.1. Depending on the number of choice tasks generated, these may be allocated to different versions so that respondents are not overwhelmed by the number of tasks that they are asked to complete. Following established guidelines, such as those from the ISPOR taskforce (Bridges et al. 2023) can ensure high-quality survey development and appropriately designed DCEs.

Figure 4.1: Example of a choice task in a DCE

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	**Improved contouring precision** compared with manual organ contouring
Automation	**Autonomous system**	**Assistive system** Requires clinician verification and sign-off
Explanatory ability	**In-depth explanations** of AI reasoning and decisions	**In-depth explanations** of AI reasoning and decisions
Compatibility with other systems	**Separate system to the existing software and systems**	**Fully integrated system with existing software and systems**
AI impact on workload	30 minutes **longer** per patient	30 minutes **saved** per patient
Which system do you prefer?	○	○

Use of DCEs in this thesis

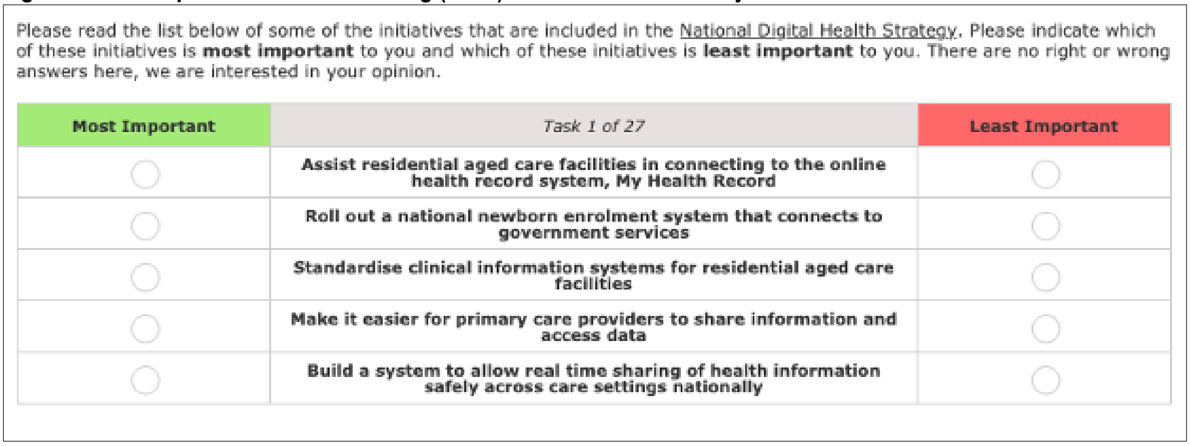
In this PhD research, two DCEs were designed and implemented to address distinct yet complementary research questions. The first DCE focused on health care professionals (HCPs) involved in radiation therapy planning, exploring their preferences for the use of AI in radiation therapy planning and delivery. The second DCE surveyed the Australian general public to understand their preferences and attitudes toward the use of AI in radiation therapy. Together, these experiments offer a comprehensive perspective on both professional clinical considerations and public perceptions regarding the use of AI in radiation oncology. The DCE is an appropriate methodological approach to address the preferences for adoption of AI in radiation oncology because there is no established market revealing preferences of patients and HCPs, given the limited information available on this relatively new market segment. AI is not one technology but rather a collection of technologies. As such it represents a multi-attribute service. The DCE design allows us to create choice options to place in choice tasks in a contingent yet realistic market to assess preferences for different features of AI.

The object case BWS

BWS, also known as maximum-difference scaling, is a multi-attribute approach to measuring preferences. It is a stated-preference method based on the assumption that respondents are capable of making judgments regarding the best and the worst out of three or more elements of a choice-set (Mühlbacher et al. 2016) . There are three types of BWS, referred to as cases, being object case, profile case and multi-profile case. The difference between these BWS types is the complexity of the items or options under consideration (Louviere et al. 2015). This chapter provides a detailed overview of the object case BWS, the methodological approach used to develop the empirical study presented in Chapter 7.

In the object case of BWS the researcher is interested in measuring a set of objects, items, statements etc on an underlying latent subjective scale (Louviere et al. 2015). Unlike in DCEs, in the BWS approach used in this thesis, object case BWS, respondents are presented with systematically generated subsets of three or more objects (items, attributes) drawn from a master list of objects and are asked, within each subset, to identify the 'best' (most preferred or most important) and the 'worst' (least preferred or least important) object. This task is repeated multiple times using subsets of items from the master list, with the subsets coming from a statistical design, allowing for robust estimation of preference structures. The number of scenarios required to identify a complete ranking depends on the number of objects and on the size of the subsets (Mühlbacher et al. 2016). An example of a BWS task appears in Figure 4.2.

Figure 4.2: Example of best-worst scaling (BWS) choice task for the object case


Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 1 of 27*	Least Important
○	Assist residential aged care facilities in connecting to the online health record system, My Health Record	○
○	Roll out a national newborn enrolment system that connects to government services	○
○	Standardise clinical information systems for residential aged care facilities	○
○	Make it easier for primary care providers to share information and access data	○
○	Build a system to allow real time sharing of health information safely across care settings nationally	○

BWS offers several advantages over pairwise comparison. First, using designed experiments, such as balanced incomplete block designs (BIBDs), can allow for a comparison of multiple objects more efficiently. Second, BWS allows two answers per set ('best' and 'worst'), which provides a more efficient presentation and collection of information (Hollin et al. 2022). BWS is particularly effective for handling a large number of objects, as it breaks down the evaluation into manageable tasks, minimising respondent fatigue and improving data quality. BWS compels respondents to prioritise by selecting the 'best' and 'worst' options from a subset of the items under consideration, providing clear and actionable preference rankings. Unlike Likert scales, which allow respondents to rate each initiative independently and often result in inflated or clustered ratings (Mühlbacher et al. 2016). BWS ensures relative differentiation among initiatives, avoiding the problem of rating everything as equally important (Mühlbacher et al. 2016). Furthermore, BWS generates preference scores that make it easy to rank initiatives objectively, offering better predictive validity and cross-respondent comparability.

These strengths make BWS a powerful tool for decision-making and resource allocation, especially when prioritising initiatives in complex contexts like health policy or business strategy (White 2021). The effectiveness of the BWS methods may be limited by the cognitive burden of too many objects, the relative nature of the scoring and potential results validity issues if the sample of respondents does not adequately represent the target population (Hollin et al. 2022). In addition, while the BWS approach can be useful for object ordering, where objects lack attribute level structure, the object ordering may lack accuracy and discriminating power in certain situations (Mühlbacher et al. 2016). However, recent studies have demonstrated BWS's particular effectiveness in healthcare policy analysis, where understanding complex prioritisation dynamics is crucial (Mühlbacher et al. 2016). Beyond healthcare, BWS methods are increasingly used in a variety of fields including agriculture, business, banking, environment, linguistics and transportation (Amiri et al. 2023; Schuster et al. 2024).

The Use of BWS in this thesis

BWS methodology was chosen as being appropriate for evaluating the alignment between the Australian National Digital Health Strategy (NDHS) on the one hand and public preferences for resource allocation on the other. BWS exercises are well suited for identifying which outcomes are critical for key decision-makers and how these may be aligned or misaligned (Irie et al. 2024). By asking respondents to select both the most and least important items within a set, BWS captures priorities and provides a quantifiable measure of relative preferences, minimising cognitive biases associated with traditional rating or ranking methods (Mühlbacher et al. 2016). This approach is particularly useful in complex decision-making contexts, such as digital health, where multiple competing priorities (e.g. interoperability, digital literacy, data analytics) must be evaluated. BWS not only facilitates the identification of shared priorities across diverse stakeholders but also highlights areas of misalignment between strategic objectives and public preferences. This allows policy-makers to make evidence-based adjustments to policies and resource allocation. It also allows one to test different scenarios to investigate how changes in priorities could affect alignment with public preferences.

The remainder of this chapter outline the key considerations in constructing designed experiments and analysing data generated from choice experiments, with a particular focus on the approaches adopted in the empirical studies presented in this thesis (Chapters 5-7).

Construction of designs for choice experiments

The construction of a designed experiment is a systematic method of generating choice tasks that are presented to respondents. It is a crucial step in choice-based studies, as it determines both the statistical efficiency of the set of choice tasks presented to respondents and the cognitive burden placed on respondents. More efficient designs give more accurate estimates using the same number of respondents, all else being equal.

DCE

A statistical design for a choice experiment refers to how attributes and levels are combined into options which are then combined into choice tasks. An effective design should provide sufficient variation across choice tasks to enable unbiased estimation of the parameters of interest, while also remaining manageable for respondents to complete (Street and Viney 2019). A statistical design for a choice experiment refers to how attributes and levels are combined into options which are then combined into choice tasks. An effective design should provide sufficient variation across choice tasks to enable unbiased estimation of the parameters of interest, while also remaining manageable for respondents to complete (Street and Viney 2019).

The first step in the generation of a designed experiment is to specify the analytical model that is going to be used to estimate the parameters of the DCE. The MNL model has been previously described as the "workhorse" of DCE estimation, and it typically serves as a starting point for basic model estimation (Street and Viney 2019). Extensions of the MNL (e.g. mixed logit, and latent class models) may be used to account for the limitations of the MNL model (see Section 4.4). The first step in the generation of a designed experiment is to specify the analytical model that is going to be used to estimate the parameters of the DCE. The MNL model has been previously described as the "workhorse" of DCE estimation, and it typically serves as a starting point for basic model estimation (Street and Viney 2019). Extensions of the MNL (e.g. mixed logit, and latent class models) may be used to account for the limitations of the MNL model (see Section 4.4).

The next step in model specification is deciding whether main effects only, or main effects and interaction effects, including between which pairs of attributes, will be included. Main effects investigate the effect of each attribute level, independent of all other attribute levels, on the choice. If the effect on the choice made at one level of an attribute depends on the level of another attribute, then we say that the two attributes interact. In this thesis, given the novel nature of the research on the uptake of AI in radiation therapy and the lack of empirical evidence to suggest the presence of potential interactions between attributes, we decided to only look at main effects.

During the construction of a designed experiment, hypothetical alternatives are generated and combined to form choice tasks based on the selected attributes and levels. Unlabelled alternatives, which describe options only in terms of their attributes and levels and without an identifying label, are most commonly used in health economics and were adopted in this thesis. The choice tasks may be presented with full or partial profiles and with or without an opt-out option. A full-profile design presents all attributes for the alternatives in each choice task. In contrast, a partial-profile DCE omits certain attributes from some alternatives. To better reflect real-world decision-making, a neutral option ('neither' or 'status-quo'), commonly referred to as an opt-out alternative (Szinay et al. 2021) is also included. This option can be presented either as part of the choice task or as a follow-up question. The DCEs presented in Chapters 5 and 6 employed forced choice full-profile designs, but allowed for possible overlap between attribute levels. The opportunity to opt-out was incorporated through a follow-up question, asking whether the respondent would instead prefer the status quo, suitably described. As the number of attributes, alternatives, options and choice tasks increases, so does task complexity. This raises concerns about cognitive burden, which can be mitigated through techniques such as blocking. Blocking partitions a large designed experiment into smaller, equal-sized subsets so that each respondent only completes a fraction of the total set of choice tasks (Szinay et al. 2021). Efficient designed experiments maximise the precision of estimated choice model parameters for a given number of choice tasks (Szinay et al. 2021). As the number of attributes, alternatives, options and choice tasks increases, so does task complexity. This raises concerns about cognitive burden, which can be mitigated through techniques such as blocking. Blocking partitions a large designed experiment into smaller, equal-sized subsets so that each respondent only completes a fraction of the total set of choice tasks (Szinay et al. 2021). Efficient designed experiments maximise the precision of estimated choice model parameters for a given number of choice tasks (Szinay et al. 2021).

A full factorial design includes all possible combinations of the attributes and levels and can be used to provide the options that can be grouped into choice tasks for the DCE. It is the grouping of these options into sets of choice tasks, and the choice of tasks to include in the DCE, that determines whether the DCE can allow for the estimation of main effects only, or main effects and any desired interaction effects. In general, one cannot present respondents with all possible combinations of options as that results in a large number of choice tasks, many of which provide little useful information (Street and Viney 2019). For instance, a design with 5 attributes with 3 levels presented in choice tasks with 2 alternatives would generate 29,403 possible choice tasks, being 3^5 possibilities for the first item, (3^5-1) for the second item and since the order of presentation of the items in an unlabelled choice task is immaterial, only one of each ordered pair of items is required. Administering such a design would clearly be impossible. To address this, researchers commonly reduce the number of choice tasks by selecting a subset of choice tasks that enable the desired models to be estimated and compare such subsets of choice tasks using an optimality measure to determine which is the best (Street and Viney 2019).

The most widely used optimality criterion in DCE design is D-optimality. The D-optimality criterion minimises the joint confidence sphere around the complete set of estimated model parameters by maximising the determinant of the inverse of the variance-covariance matrix in maximum-likelihood estimation. Algorithms can be used to construct D-optimal designs, and a corresponding D-efficiency score provides a quantitative measure of design quality (Johnson et al. 2013).

Most available software solutions for constructing designed experiments use algorithms to construct D-optimal designs for the smallest possible design that identifies all the necessary parameters. The DCEs presented in this thesis (Chapters 5 and 6) employed a D-optimal design generated using the idefix package in R Studio (Traets et al. 2020), which specified choice tasks (allocated across survey versions) for direct implementation in the experiment. Blocking was applied to reduce respondent burden and improve response quality.

BWS

The construction of designed experiments in a BWS tells us which objects (object code numbers, referred to as items) to put in each choice task. BWS experiments with a large number of items may put additional burden on respondents. “In a standard best-worst experiment where we want to show each item three times, one can determine the appropriate number of number of questions, depending on the total number of items using simple math, multiplying three times the number of items in the study and dividing by the number of items per question. Increasing the total number of items increases the number of questions per respondent, and thus the length of the survey, at some point adversely affecting the quality of responses” (Chrzan and Peitz 2019).

To accommodate a large number of items, sparse and express BWS methods can be applied. Sparse BWS is a preferred method for handling a large number of items (Chrzan and Peitz 2019). “Express BWS shows different respondents different subsets of the items; each respondent sees each of the items in her subset (and only those items) three or four times. For example, in a study of 100 items, we might randomly select a unique subset of 24 items for each respondent. Each respondent receives

18 choice tasks of four items each, with each of the 24 items in her unique subset presented in three choice tasks, and with none of the other 76 items presented. Each respondent receives a different subset of items, but across respondents, every item would be included in some respondents' subsets. A Sparse BWS, on the other hand, allows each item to appear as infrequently as just once across each respondent's BWS questions (rather than the previously suggested three to four times). To continue the example study of 100 items, we might, with a Sparse BWS experiment, show each respondent 20 sets of five items each. A given respondent would see all 100 items, with each item appearing in exactly one choice task. Different respondents would receive different blocks of the experimental design, allowing each item to appear with all the other items as well as enabling us to control for order and position effects" (Chrzan and Peitz 2019).

The BWS study presented in Chapter 7 was a sparse BWS using a Balanced Incomplete Block Design (BIBD), which is the type of design most commonly used in object case BWS studies (Hollin et al. 2022).
The BWS study presented in Chapter 7 was a sparse BWS using a Balanced Incomplete Block Design (BIBD), which is the type of design most commonly used in object case BWS studies (Hollin et al. 2022).
A BIBD is constructed on a set of v items by finding b subsets, or blocks, each containing k distinct items, such that each item appear in exactly r blocks and each pair of items appears in exactly λ of the b blocks. The blocks of the BIBD can be used as the choice tasks of the BWS object case.

Models for choice data analysis

The analysis of data form choice -experiments is based on Lancaster's theory of value, which assumes that utility is derived from the underlying characteristics of the options being presented (Lancaster and Tsushima 1966) and on the random utility model (RUM) (McFadden, D. 1974; Train 2009). The underlying choice process is utility maximisation, which assumes that each respondent will choose, from the options available, the one which has the higher/highest utility (for them) (Street and Viney 2019).

As mentioned above, the choice of model for analysing the choice experiment results must be considered during the design phase, as the model determines the information matrix, and functions of the information matrix are commonly used to evaluate and compare different designs (Street and Viney 2019). Furthermore, for any choice model, the information matrix depends not only on the model itself but also on the unknown parameters. Therefore, it is important to consider how well the proposed design is likely to perform across a range of plausible parameter values (Street and Viney

2019)As mentioned above, the choice of model for analysing the choice experiment results must be considered during the design phase, as the model determines the information matrix, and functions of the information matrix are commonly used to evaluate and compare different designs (Street and Viney 2019). Furthermore, for any choice model, the information matrix depends not only on the model itself but also on the unknown parameters. Therefore, it is important to consider how well the proposed design is likely to perform across a range of plausible parameter values (Street and Viney 2019). The two most common models used for the analysis of choice experiments in health economics are the multinomial logit (MNL) and the mixed logit (MXL) model, each accounting for 39% of DCEs reported between 2013-2017 (Soekhai et al. 2019). The models presented in this section build directly on the contributions of Sarrias and Daziano (2017), Hensher (2015), and Street and Viney (2019), as referenced in the corresponding subsections of this thesis.

Multinominal logit (MNL)

In a DCE, if choice task c consists of multiple (m) options $T_{1c,\dots,}$ T_{mc} , with corresponding utility function U_{ic} , $1 \leq i \leq m$ then option T_{ic} is chosen if $U_{ic} > U_{jc}$ $\forall j \neq i, 1 \leq j \leq m,$ since a respondent is assumed to select the option with the highest utility.

The utility of an option is typically modelled as the sum of a systematic component, which depends on the attribute levels of the option (T_i) and a random component (e_i), which captures unobserved factors, taste variation, or measurement error (McFadden, D. 1974; Train 2009). Thus:

$$U_i = V_i + e_i \ . \qquad \text{(Equation 1)}$$

When the choices are made according to the Random Utility Model (RUM) principle and the random components are assumed to be independent and follow a Type 1 extreme value distribution, the resulting model is the multinomial logit (MNL), where the probability of choosing a given option is determined by the relative systematic utilities of all options in the choice task (Train 2009). In this case, the probability of choosing T_i is given by the logit formula:

$$P(T_i > \{T_1, T_2, \dots T_m\}) = \frac{exp(\lambda V_i)}{\sum_{j=1}^{m} exp(\lambda V_j)}, \qquad \text{(Equation 2)}$$

where λ is a positive scale parameter inversely related to the variance of the random component. Since λ cannot be estimated separately from the coefficients, it is commonly set to 1.

As presented in Street and Viney (2019): "suppose each T_i is represented by a k-tuple (t_{i1},..., t_{ik}) where t_{iq} is the level of attribute q, 1 ≤ q ≤ k, . If attribute q has l_q levels (represented by 0, 1, ..., l_q-1), we must code these levels if we are fitting the attribute as a categorical variable when calculating V_i. This can be done with dummy or effects coding. In dummy coding, one level is omitted, the so-called reference level, and represented by a vector of zeros, of length l_q-1 while the remaining levels are coded as rows of the identity matrix of order l_q-1. In effects coding, the reference level is represented by a vector of –1s of length l_q-1, with other levels again corresponding to the rows of an identity matrix of order l_q-1. The systematic utility for each option is then expressed as a linear combination of these coded attributes and a vector of parameters which need to be estimated. However, we do the coding we will represent the resulting vector associated with T_i by the row with vector x_i. For a main effects model, the length of each x_i is: $\sum_{q=1}^{k}(l_q - 1)$ = p; and we have $V_i = x_i\beta$, where β is a column vector of length p of the parameters to be estimated.

When interactions terms are included (e.g. for a two-way interaction between attributes q and r), additional entries are adjoined to x_i. In the case of two-way interactions between attributes $p$and q, the number of extra terms is $(l_q - 1)(l_r - 1)$. Thus, the total length of x_i is the sum of the main-effect terms and the interaction terms, with a corresponding increase in the length of β but we will always assume that there are p parameters to estimate.

The Fisher information matrix of the C, choice tasks which make up design d, is given by:

$$M_{dn\beta} = \sum_{c=1}^{C} X'_c \left(diag(p_{c,\beta}) - p_{c,\beta}p'_{c,\beta}\right) X_c. \qquad \text{(Equation 3)}$$

where $p_{c,\beta}$ is the vector of choice probabilities for the entries in choice task c given the column of parameters β and X_c is a matrix of order $c \times p$ which has the x_i associated with the options in choice task c as its rows. This is the information matrix for a single respondent and, assuming all respondents see the same choice tasks, the overall DCE information matrix is obtained by summing over the respondents.

Mixed logit (MXL)

The MXL model relaxes the assumption of the multinomial logit model, allowing unobserved heterogeneity to be modelled by permitting each individual to have their own set of parameters which are assumed to come from some underlying distribution (Sarrias and Daziano 2017). The model explicitly assumes that there is a distribution of preference weights across the sample reflecting differences in preferences among respondents, and it models the parameters of that distribution. In this thesis a normal distribution is assumed and so estimating the mean and standard deviation is sufficient, since these parameters uniquely characterize the normal distribution. The MXL model assumes that the elements of β are random effects (Street and Viney 2019) where:

$$\beta = \mu + Z\sigma \,, \qquad \text{(Equation 4)}$$

where $\mu = (\mu_1, \mu_2, \dots, \mu_p)$ represents the mean preference vector, $\sigma = (\sigma_1, \sigma_2, \dots, \sigma_p)$ represents the standard deviations and Z is a *p x p* diagonal matrix whose entries are independently and identically distributed random variables from the standard normal distribution.

The MXL model estimates a set of mean preference weights and a set of standard deviations of effects across the sample. Interpretation of mean preference weights is made in relation to a base level for each attribute. The standard deviations indicate variability in the mean preference weights; larger (smaller) values indicate greater (smaller) variability (Hauber et al. 2016).

The mixed logit model is defined on the basis of the functional form for its choice probabilities, given by (Train 2009):

$$P_{ni} = \int L_{ni}(\beta) f(\beta) d\beta, \qquad \text{(Equation 5)}$$

where $L_{ni}(\beta)$ is the logit probability evaluated at parameter β:

$$L_{ni}(\beta) = \frac{\exp\left(V_{ni}(\beta)\right)}{\sum_{j=1}^{J} \exp\left(V_{nj}(\beta)\right)}, \qquad \text{(Equation 6)}$$

and $f(\beta)$ is the density function. $V_{ni}(\beta)$ is the observed portion of the utility, which depends on the parameter β. If the utility is linear in β, then $V_{ni}(\beta) = \beta' x_{ni}$. In this case, the mixed logit probability is expressed in the form (Train 2009):

$$P_{ni} = \int \left(\frac{\exp\left(\beta' x_{ni}\right)}{\sum_j \exp\left(\beta' x_{nj}\right)}\right) f(\beta) d\beta \,. \qquad \text{(Equation 7)}$$

The mixed logit probability is a weighted average of the logit formula evaluated at different values of β, with the weights given by the density $f(\beta)$. The MNL is a special case where the weights given by $f(\beta)$ are b: $f(\beta)$= 1 for β = b and 0 for $\beta \neq b$. The choice probability (Equation 7) then becomes the logit formula (Train 2009):

$$P_{ni} = \frac{\exp\,(b' x_{ni})}{\sum_j \exp\,(b' x_{nj})}, \qquad \text{(Equation 8)}$$

and, which is the same for all individuals.

The weights given by $f(\beta)$ can be non-zero at only a finite number of points, corresponding to β taking a finite set of distinct values (Train 2009). This gives rise to the latent class model which we discuss next.

Latent class model (LC)

Another approach to explore preference heterogeneity in the data is to use a Latent Class (LC) model. It is a special case of the mixed logit model, which is useful if the sample population consists of several segments (classes), each with its own preferences. Latent class analysis is used to identify latent classes within a population based on individuals' responses to various choice tasks. Latent class models relax the assumption of homogeneous preferences and assume there are two or more classes or groups (segments) of people with homogenous preferences within each group (Shen 2009).
The group membership variable is latent (unobserved) and while it can be related to a set of discrete observed measures such as general attitudes and perceptions as well as sociodemographic characteristics of the individuals, in this thesis (Chapter 7) we only use the choices made to identify the classes (Shen 2009).The group membership variable is latent (unobserved) and while it can be related to a set of discrete observed measures such as general attitudes and perceptions as well as sociodemographic characteristics of the individuals, in this thesis (Chapter 7) we only use the choices made to identify the classes (Shen 2009).

Suppose individual n faces choice task c. Assuming that the person belongs to class g, the probability of choice i is (Hensher et al. 2018):

$$P_{nc|g}(i) = \frac{\exp(x_{nci}\beta_g)}{\sum_{j=1}^{m} \exp(x_{ncj}\beta_g)}. \qquad \text{(Equation 9)}$$

If we let y_{nc} be the choice made by individual n in choice set c then individual n has the sequence of choices $y_n = (y_{n1}, \dots, y_{nC})$. Then, conditional on class g, (Hensher et al. 2018):

$$P_{n|g} = \prod_{c=1}^{C} P_{nc|g}. \qquad \text{(Equation 10)}$$

Since class assignments are unknown, the probability that individual n belongs to class g is modelled as (Sarrias and Daziano 2017):

$$\omega_{ng} = \frac{\exp(\gamma_g)}{\sum_{j=1}^{G} \exp(\gamma_j)}, g = 1, \dots, G, \gamma_1 = 0, \qquad \text{(Equation 11)}$$

where the γ_g are constants.

The likelihood for individual n is the expectation (over classes) of the class-specific contribution, as shown (Hensher et al. 2018):

$$P_n = \sum_{g=1}^{G} \omega_{ng} P_{n|g}. \qquad \text{(Equation 12)}$$

The log-likelihood (LL) for the sample is (Hensher et al. 2018):

$$lnL = \sum_{n=1}^{N} lnP_n = \sum_{n=1}^{N} ln\left[\sum_{g=1}^{G} \omega_{ng} (\prod_{c=1}^{C} P_{nc|g})\right]. \qquad \text{(Equation 13)}$$

The appropriate number of classes, G, that allows us to capture the true heterogeneity can be based on either the Akaike Information Criterion (AIC) or the Bayesian Information Criterion (BIC) (Stata 2025):

$$AIC = -2lnL + 2(p\,G + (G-1)), \qquad \text{(Equation 14)}$$

$$BIC = -2lnL + 2(p\,G + (G-1))ln(NC), \qquad \text{(Equation 15)}$$

where lnL is maximised log-likelihood, $(p\,G + (G-1))$ is the number of parameters estimated, NC is number of observations from N respondents, each providing C choices. In models with latent G classes, the number of parameters is $p\,G + (G-1)$, since each class has p parameters, and $(G-1)$ γs to estimate the class membership probabilities.

While the AIC and BIC are two popular measures for comparing maximum likelihood models, they each have distinct theoretical advantages. Thus, a researcher may judge that there may be a practical advantage to one or the other in some situations. For example, as mentioned earlier, in choosing the number of classes in a mixture model, the true number of classes required to satisfy all model assumptions is sometimes quite large, too large to be of practical use or even to allow coefficients to be reliably estimated. In that case, BIC would be a better choice than AIC. Additionally, in practice, one may wish to rely on substantive theory or parsimony of interpretation in choosing a relatively simple model (Dziak et al. 2020).

Once the parameters are estimated, we can compute the probability that individual n belongs to class g, conditional on their observed choices. These posterior class probabilities are obtained via Bayes' theorem and given by (Hensher et al. 2018):

$$\hat{\omega}_{ng} = \frac{\hat{P}_{ng}\hat{\omega}_{ng}}{\sum_{g=1}^{G}\hat{P}_{ng}\hat{\omega}_{ng}}, \qquad \text{(Equation 16)}$$

where $\hat{\omega}_{ng}$ is used to indicate the respondents-specific estimate of the class probability, conditioned on their estimated choice probabilities, as distinct from the unconditional class probabilities that enter the LL function. This posterior probability reflects how likely each individual is to belong to a given class and it forms the basis for class assignment, as well as for the calculation of class specific parameter estimates. Membership of a particular class may be characterised by shared observed demographic characteristics that determine choice, or by other unobserved factors that drive preferences. These can be investigated once the classes based on the choices made have been identified.

Multinomial probit model (MNP)

The multinomial probit model, instead of utilising the logistic function as in the multinomial logit model, employs the cumulative distribution function of the standard normal distribution, the probit function to estimate the probabilities of each category. The MNP model assumes that the error terms associated with each alternative follow a multivariate normal distribution, allowing for more flexible distributional assumptions compared to the MNL model. Like the MNL model, each outcome category in the MNP model has its own set of parameters, capturing the influence of predictor variables on the likelihood of choosing that category (Hensher et al. 2018).

Willingness-to- pay

In economics, the marginal rate of substitution is the amount of one good that a consumer is willing to give up in exchange for a new good, while maintaining the same level of utility (Mott et al. 2020).

The approach for estimating MRS using DCE data is to take the ratio of the 2 estimated attribute level coefficients of interest, as in the equation below (Mott et al. 2020).

$$MRS_{xy} = \left(\beta_x/\beta_y\right), \qquad \text{(Equation 17)}$$

where MRS_{xy} is the trade of between attribute levels x and y, and β_x and β_y are their coefficients in the choice model.

BWS data analysis

The principles underlying the analysis of the best-worst choice data are similar to those in a discrete choice experiment, and the theoretical framework common to both is random utility theory, which assumes that people make errors, but when choosing repeatedly their choice frequencies give an indication of how much they value the items under consideration (Louviere et al. 2015). Thus, how often item A is chosen over item B gives an indication of how much item A is preferred to item B. This information is obtained from how often respondents select item A as best and/or item B as worst in the presented choice tasks (Louviere et al. 2015). The principles underlying the analysis of the best-worst choice data are similar to those in a discrete choice experiment, and the theoretical framework common to both is random utility theory, which assumes that people make errors, but when choosing repeatedly their choice frequencies give an indication of how much they value the items under consideration (Louviere et al. 2015). Thus, how often item A is chosen over item B gives an indication of how much item A is preferred to item B. This information is obtained from how often respondents select item A as best and/or item B as worst in the presented choice tasks (Louviere et al. 2015).

As a first approximation, we calculate the individual best-worst scores by counting how many times each object is chosen as best and how many times it is chosen as worst, then subtract the worst count from the best count. These differences are then normalised to lie between -1 and +1 by dividing by the number of times each object appeared (its availability). This normalised score provides a meaningful individual-level measure of preference or importance, where +1 indicates the item was always chosen as best every time that it was presented, and -1 means it was chosen as worst every time that it was presented (Louviere et al. 2015). These count-based results provide an initial indication of preference ordering and can inform subsequent statistical modelling.

To extract more detailed preference information from BWS data, statistical models based on random utility theory can be employed, most commonly the multinomial logit (MNL) and mixed multinomial logit (MXL) models. In both model types, the observed choice data are used to estimate the probability of selecting particular objects as best or worst, based on the difference in latent utility. For the MNL, these probabilities follow a logistic distribution. For the MXL, individual-level variation is modelled, typically assuming normally distributed random coefficients. Each choice scenario is treated as a set of alternatives, with the respondent choosing the most and least preferred object from each set. The BWS task is modelled as a series of paired comparisons, where the probability of each best-worst (or most-least) combination is a function of the utility difference between chosen objects. The standard MNL model assumes homogenous preferences across respondents. It estimates utility coefficients for each object based on the observed pattern of best and worst choices. The MXL (mixed logit) model relaxes this assumption by allowing for random variation in utility coefficients across respondents, accommodating preference heterogeneity within the sample.

Before estimating the MNL or MXL model, MaxDiff data must be transformed into a choice-modelling format suitable for logit estimation. First, a respondent–task–item level dataset is created where the independent variable is coded as 1 if the item was selected as best, −1 if selected as worst, and 0 otherwise. The independent variables consist of item-specific dummy variables. In this structure, each best–worst decision contributes several observations to the likelihood function, allowing the model to estimate utility coefficients that reflect the relative preference for each item while accounting for the full choice context (Louviere et al. 2015). For example, if a respondent evaluates a set of four items {A, B, C, D} and selects A as best and D as worst (Table 1), this yields six paired comparisons: A vs B, A vs C, A vs D, B vs D, C vs D, and B vs C (coded as 0 for items not chosen), which are used to construct the data used for the log-likelihood for estimation (Table 2).

Table 4.1: Item-level representation of a best–worst task

Respondent	Task	Item	Choice	Notes
1	1	A	1	Best
1	1	B	0	Not chosen
1	1	C	0	Not chosen
1	1	D	−1	Worst

The MaxDiff representation of this is given in Table 4.2 below:

Table 4.2: MaxDiff representation of data

A	B	C	D	Choice
1	-1	0	0	0
1	0	-1	0	0
1	0	0	-1	1
0	1	-1	0	0
0	1	0	-1	0
0	0	1	-1	0
-1	1	0	0	0
-1	0	1	0	0
-1	0	0	1	0
0	-1	1	0	0
0	-1	0	1	0
0	0	-1	1	0

It is this representation of BWS data that was used in Chapter 7 of this thesis.

Chapter 5: Preferences for adopting artificial intelligence in radiation therapy treatment: A discrete choice experiment with health professionals

Publication details

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Ethics approval for the DCE was obtained from the University of Technology Sydney Human Research Ethics Committee as part of the CHERE's program ethics (HREC Reference No. 21-6090; Figure A5.1, Appendix 5). Respondent confidentiality was ensured by anonymising the data entry in the survey. All respondents provided informed consent. Respondents had the right to withdraw from the study at any time and without giving reasons and to request the deletion of the collected data at any time during the survey. Respondents were informed that they could contact the Research Office directly if they had any concerns, they wished to raise independently of the research team. Both a phone number and an email address were provided for this purpose. Researchers' contact information was provided on the first and last page in case the respondents had questions. The respondents could contact the researchers directly by phone or via a contact email address. The respondents were told that the results of this study could be presented at national and international conferences and published in peer-reviewed journals.

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%) (AIHW 2021). The Australian Institute of Health and Welfare (AIHW) estimates 1.9 million cases of cancer will be diagnosed between 2024 and 2033 (AIHW 2024a). 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 (AIHW 2024b). 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 (Mun and Dieterich 2023). 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 (Santoro et al. 2022). 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 (Mun and Dieterich 2023). 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 (Santoro et al. 2022).

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 (Khalifa and Albadawy 2024). There is increasing research showing that AI achieves superior accuracy compared to processes primarily reliant on human input. AI in auto-contouring compared with a human practitioner shows improved performance in terms of precision, differences in dose distribution, and time consumption (Marin Anaya 2023; Sarria et al. 2023).

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 (Topol 2019). 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 (Topol 2019). 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.

Understanding not only the potential the benefits of AI-based innovations but also their potential adverse effects, such as overdiagnosis and increased healthcare utilisation is important for successful integration into healthcare system (Senevirathna et al. 2023).

The key opportunities and limitations associated with the adoption of AI in healthcare are outlined below, providing essential context for the development of the discrete choice experiments (DCEs).

AI Accuracy

Accuracy in healthcare is as a cornerstone of patient safety and clinical excellence, preventing misdiagnoses and inappropriate interventions that could result in adverse outcomes or mortality. This precision in clinical information not only fulfils legal and ethical obligations but also enhances operational efficiency by minimising redundant testing and interventions. The accuracy of AI refers to the degree to which an AI system correctly performs its intended tasks or makes correct predictions based on input data (Mun and Dieterich 2023). AI systems have demonstrated exceptional accuracy in specific healthcare domains (Alowais et al. 2023). They excel particularly in tasks requiring sustained attention and pattern recognition, such as identifying subtle abnormalities in medical images that may elude human perception. Growing evidence indicates that AI can outperform human clinicians in detecting various cancers, including lung, liver, and breast malignancies (Ge et al. 2024; Lång et al. 2023). 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 more successfully performed by AI compared with manual methods (Polymeri et al. 2024). A landmark randomised controlled trial (RCT) involving 80,000 women found that radiologists using AI detected 20% more breast cancers while reducing screen-reading workload by 44.3% compared to conventional approaches (Lång et al. 2023).

Data Quality and Representational Fairness

The reliability and safety of clinical AI applications depend on the quality and generalisability of training data. AI systems can only be as accurate as the data they're trained on, and many healthcare datasets contain historical biases, are incomplete, or lack diversity across demographics, conditions, and care settings (McCradden, Sarker, et al. 2020). Systems developed using incomplete, inaccurate, or non-diverse datasets risk perpetuating or amplifying existing healthcare disparities. Research has consistently shown that AI models often perform unequally across demographic groups, with women and people of colour frequently experiencing the most significant disadvantages (Watkins et al. 2022; Temple and Rowbottom 2024; McCradden, Joshi, et al. 2020). These representational biases can manifest as differential diagnostic accuracy across population subgroups, inappropriate treatment recommendations, or inability to generalise to novel clinical presentations. The consequences of such algorithmic shortcomings extend beyond technical performance metrics to potentially exacerbate existing healthcare disparities, particularly affecting traditionally underserved populations whose characteristics may be underrepresented in training data. 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 (Nazer et al. 2023). Responsible AI deployment therefore requires rigorous understanding of data source, quality assessment protocols, and applicability across intended patient populations (McCradden, Joshi, et al. 2020). The reliability and safety of clinical AI applications depend on the quality and generalisability of training data. AI systems can only be as accurate as the data they're trained on, and many healthcare datasets contain historical biases, are incomplete, or lack diversity across demographics, conditions, and care settings (McCradden, Sarker, et al. 2020). Systems developed using incomplete, inaccurate, or non-diverse datasets risk perpetuating or amplifying existing healthcare disparities. Research has consistently shown that AI models often perform unequally across demographic groups, with women and people of colour frequently experiencing the most significant disadvantages (Watkins et al. 2022; Temple and Rowbottom 2024; McCradden, Joshi, et al. 2020). These representational biases can manifest as differential diagnostic accuracy across population subgroups, inappropriate treatment recommendations, or inability to generalise to novel clinical presentations. The consequences of such algorithmic shortcomings extend beyond technical performance metrics to potentially exacerbate existing healthcare disparities, particularly affecting traditionally underserved populations whose characteristics may be underrepresented in training data. 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 (Nazer et al. 2023). Responsible AI deployment therefore requires rigorous understanding of data source, quality assessment protocols, and applicability across intended patient populations (McCradden, Joshi, et al. 2020).

Transparency and Explainability Challenges

The AI algorithms may lack interpretability or transparency in their decision-making processes, the phenomenon referred to as being a "black box" (Ahmed et al. 2023). Lack of understanding of the AI systems decision-making 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 (Ahmed et al. 2023). Making sure that AI systems can explain their decisions is also important for building trust among healthcare professionals, mitigating concerns about algorithmic bias and to account for potential liability issues. While transparency and explainability generally enhance trust, they are not universally achievable with current technologies. Therefore, these attributes should be understood as mechanisms for building confidence rather than absolute requirements (Walsh 2022). For clinicians, explainability serves as a means to justify clinical decision-making in the context of AI predictions. Research indicates that healthcare professionals may accept models with lower accuracy provided there is clarity regarding when and why the model might underperform (Tonekaboni et al. 2019).

Professional identity and impact on workforce

The integration of AI into clinical practice raises concerns about potential workforce de-skilling, reduced autonomy, discretion, and clinical judgment, particularly in specialties that rely heavily on pattern recognition such as radiology. While technological disruption in healthcare is not unprecedented, as seen with electronic health records and telemedicine, AI-driven automation presents unique challenges to professional identity and clinical expertise (Schneider-Kamp and Godono 2025). The concern extends beyond simple task automation to potentially degrading clinical services through diminishing the holistic nature of clinical reasoning, which incorporates intuition, emotional intelligence, and contextual understanding. AI systems that lack transparency may further undermine clinician confidence and professional identity, highlighting the need for transparent AI technologies that support rather than replace clinical expertise (Goktas and Grzybowski 2025).

Interoperability and Systems Integration

Interoperability of AI's technologies in healthcare requires standardised data exchange between systems within and across organisations while maintaining data privacy and security. Different technological platforms and varying levels of technological maturity across healthcare settings create additional integration complexities (Ahmed et al. 2023). Furthermore, many healthcare organisations rely on legacy IT systems that were not designed to support modern AI technologies. Upgrading or replacing these systems to accommodate AI can be complex and costly. Integration challenges include ensuring interoperability between new AI systems and existing electronic health records (EHRs), maintaining data integrity, and minimising disruptions to patient care during the transition. These complexities can delay the implementation of AI solutions and require significant technical expertise. In specialised fields like radiotherapy planning, AI systems can be implemented as either stand-alone or integrated solutions. Stand-alone systems focus on specific tasks like organ auto-contouring and image segmentation. This offers the flexibility to use these systems through interfaces of various treatment planning platforms (Rusanov et al. 2025). Integrated systems incorporate AI directly into existing radiotherapy workflows, enabling real-time adaptation and enhanced imaging capabilities (Najjar 2023). However, concerns persist about how these technologies might impact creativity, clinical oversight, and professional identity within radiation oncology (Jones et al. 2024). However, concerns persist about how these technologies might impact creativity, clinical oversight, and professional identity within radiation oncology (Jones et al. 2024).

Regulatory and implementation issues

Implementing AI in healthcare involves navigating several regulatory and practical challenges. These challenges can significantly impact the adoption and effectiveness of AI technologies in clinical settings. The rapid advancement of AI technologies has outpaced the development of comprehensive regulatory frameworks and guidelines. This gap creates uncertainty for healthcare providers and developers regarding compliance with existing laws and standards. Regulatory bodies are still working to establish clear guidelines for the safe and ethical use of AI in healthcare, which includes ensuring patient privacy, data security, and the reliability of AI algorithms (AHPRA 2025). The Australian Department of Health and Aged Care consultation, "Safe and Responsible Artificial Intelligence in Health Care – Legislation and Regulation Review" outlines key opportunities and challenges for AI in healthcare. Drawing on recent research, the Productivity Commission highlights AI's potential to boost productivity, the importance of leveraging existing regulatory frameworks, and the need for a national data strategy to improve data sharing, particularly by addressing barriers in the private sector and embedding Indigenous data sovereignty from the outset (Australian Government, Productivity Commission 2024).

The lack of standardised regulations can hinder the widespread adoption of AI technologies, as organisations may be hesitant to invest in systems that could face future regulatory challenges or that sacrifice data security and patient safety. In addition, integrating AI into existing healthcare workflows requires substantial upfront investment. These costs include purchasing AI software, upgrading hardware, training staff, and potentially hiring new personnel with specialised skills (Ahmed et al. 2023). The financial burden can be a significant barrier, especially for smaller healthcare facilities with limited budgets. Once AI systems are deployed, continuous monitoring is necessary to ensure they function correctly and safely. Post-deployment monitoring involves tracking the performance of AI algorithms, identifying and addressing any issues that arise, and ensuring compliance with regulatory standards. This ongoing process requires dedicated resources and can be resource-intensive (Kolla and Parikh 2024). The lack of standardised regulations can hinder the widespread adoption of AI technologies, as organisations may be hesitant to invest in systems that could face future regulatory challenges or that sacrifice data security and patient safety. In addition, integrating AI into existing healthcare workflows requires substantial upfront investment. These costs include purchasing AI software, upgrading hardware, training staff, and potentially hiring new personnel with specialised skills (Ahmed et al. 2023). The financial burden can be a significant barrier, especially for smaller healthcare facilities with limited budgets. Once AI systems are deployed, continuous monitoring is necessary to ensure they function correctly and safely. Post-deployment monitoring involves tracking the performance of AI algorithms, identifying and addressing any issues that arise, and ensuring compliance with regulatory standards. This ongoing process requires dedicated resources and can be resource-intensive (Kolla and Parikh 2024).

Ethical Considerations in Clinical AI

The use of AI in healthcare settings raises fundamental ethical questions that need careful consideration. One major concern is ensuring fairness and equitable access, as AI technologies must be accessible to all patients regardless of socioeconomic status to avoid exacerbating existing health disparities. Additionally, there is the potential for over-reliance on technology, which could lead to a diminished role for human judgment and expertise in patient care. This could also lead to de-humanising patient care, where the personal touch and empathy provided by healthcare professionals is replaced by automated systems. However, published research has shown that AI-based assistants (i.e., chatbots) may be preferred by patients in certain settings, with responses rated significantly higher in both quality and empathy compared to those provided by physicians (Chen et al. 2025; Ayers et al. 2023). The use of AI in healthcare settings raises fundamental ethical questions that need careful consideration. One major concern is ensuring fairness and equitable access, as AI technologies must be accessible to all patients regardless of socioeconomic status to avoid exacerbating existing health disparities. Additionally, there is the potential for over-reliance on technology, which could lead to a diminished role for human judgment and expertise in patient care. This could also lead to de-humanising patient care, where the personal touch and empathy provided by healthcare professionals is replaced by automated systems. However, published research has shown that AI-based assistants (i.e., chatbots) may be preferred by patients in certain settings, with responses rated significantly higher in both quality and empathy compared to those provided by physicians (Chen et al. 2025; Ayers et al. 2023).

Another critical issue is the appropriate allocation of decision-making responsibility. This requires clear definition of the roles of AI and human practitioners to maintain accountability and trust. 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. Trust in a clinical context refers to the confidence a patient has in their healthcare provider, believing that the provider will act in their best interest, possess the necessary expertise and make informed decisions regarding their health (Birkhäuer et al. 2017) The use of AI technologies in clinical settings may impact on these components of trust. Finally, the early identification of algorithmic harms, often referred to as the "canary in the coal mine", is crucial to promptly address any unintended negative consequences of AI deployment, ensuring patient safety and ethical integrity in clinical practice (McCradden 2024).

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 (Chew and Achananuparp 2022). 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 (O'Shaughnessey and Collins 2023). 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 (Duffy 2022). 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 (Shinners et al. 2020; Batumalai et al. 2020; Brouwer et al. 2020; Castagno and Khalifa 2020; O'Shaughnessey and Collins 2023; Coakley et al. 2022), studies utilising stated preference (SP) 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 DCE, which is a quantitative SP method. DCE is a method of eliciting SPs 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 (Ryan et al. 2008). DCEs allow to understand how people trade-off between different features of the objects being compared, in this study, two AI systems. A detailed description of the SP methodology is provided in Chapter 4 of this thesis.

Choice experiments are widely used in transport economics, environmental economics, marketing, and health economics (Broberg et al. 2021; Cao 2021; Godden et al. 2023; Hellali et al. 2023; Schatzmann et al. 2024). DCEs are increasingly popular in evaluation of digital health technologies (DHTs) across a wide range of health-related concerns (Vo et al. 2024). 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. Choice experiments are widely used in transport economics, environmental economics, marketing, and health economics (Broberg et al. 2021; Cao 2021; Godden et al. 2023; Hellali et al. 2023; Schatzmann et al. 2024). DCEs are increasingly popular in evaluation of digital health technologies (DHTs) across a wide range of health-related concerns (Vo et al. 2024). 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

A DCE was designed 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 which reveals the preferences of HCPs who are involved in RT treatment planning, due to limited information on this 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.

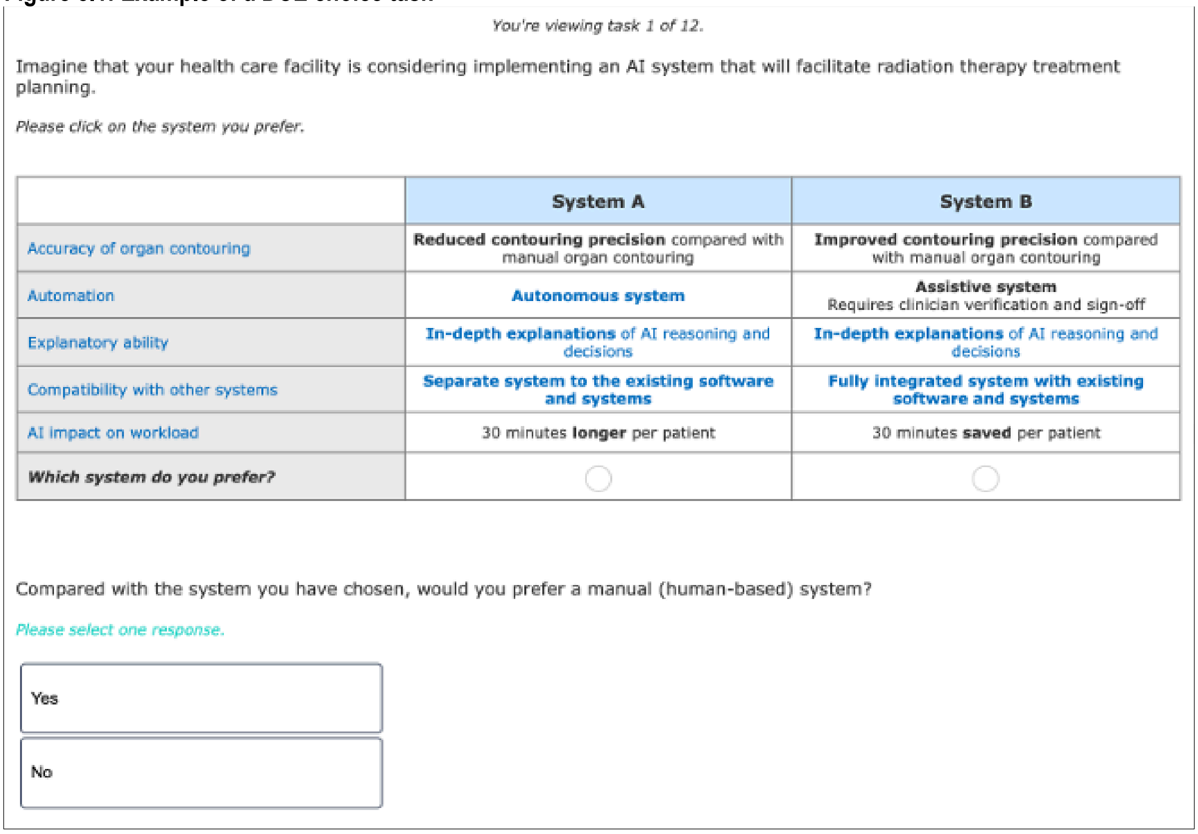
Survey development

The survey instrument was developed using the steps recommended by the Professional Society for Health Economics and Outcomes Research (ISPOR) taskforce (Bridges et al. 2023). The DCE tasks were created and refined in stages based on both qualitative and quantitative methods, with the qualitative component comprising structured consultation with expert researchers rather than primary qualitative data collection. 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 reviewed 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 Figure 5.3, Appendix 5.

Figure 5.1Figure 5.1 presents an example of the DCE choice task as presented to respondents. Each choice task started with a vignette which described how the respondent's health care facility was considering implementing an AI system to facilitate RT treatment planning. Two different systems are described in terms of their features: accuracy, automation, explainability, compatibility and impact on workload. Respondents were asked to compare the two systems-based on the attributes described and select their more preferred system. They were then asked if they would prefer the system they chose or a manual system.

Figure 5.1: Example of a DCE choice task



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	**Improved contouring precision** compared with manual organ contouring
Automation	**Autonomous system**	**Assistive system** Requires clinician verification and sign-off
Explanatory ability	**In-depth explanations** of AI reasoning and decisions	**In-depth explanations** of AI reasoning and decisions
Compatibility with other systems	**Separate system to the existing software and systems**	**Fully integrated system with existing software and systems**
AI impact on workload	30 minutes **longer** per patient	30 minutes **saved** per patient
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

Attributes and levels

The AI systems accuracy and explainability were each assigned three levels. A four-level attribute described the impact of AI on workload in terms of the 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 (Table 5.1).

Table 5.1: 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 minutes longer per patient 2. No change 3. 30 minutes saved per patient 4. 60 minutes saved per patient	The impact of AI on the time required for generating treatment plans (dosimetry) compared with a predominantly human-based system

Designed experiment

The designed experiment contained 36 choice tasks which were divided into three versions, each with 12 choice tasks. The initial *D*-optimal design was constructed using idefix (Traets et al. 2020) to select the choice options to be included in the experiment to allow for estimation of the main 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.

Data collection

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 its 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.

Data analysis

Data were analysed in R Studio 2024 (RStudio Team 2024). Descriptive statistics were used to summarise the characteristics of the overall sample. A multinomial logit model was originally fitted to the data. The marginal willingness to save time was estimated using coefficients from the multinomial logit 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 given 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.

The MIXL model was estimated using the GMNL package (Sarrias and Daziano 2017) in R Studio 2024 (RStudio Team 2024). Several variations of the MXL model were estimated to identify the model of best fit to the data. All variables were dummy coded, and each model was simulated with different numbers of Halton draws, ranging from 100 to 5000. The model estimates a set of mean preference weights and a standard deviation of effects across the sample. The model was based on the choice data assuming that the parameters follow a multivariate normal distribution with all pairwise correlations equal to 0.

The base level for each variable was used to compare the estimated coefficients of the other levels, both within and across attributes.
Heterogeneous preferences identified in the MIXL model via significant standard deviations ($p < 0.05$) were examined further via choice probability distributions and by kernel density plots.

Another approach to explore preference heterogeneity in the data is to use a LC model (Ryan et al. 2008). Latent class analysis is used to identify subgroups within a population according to individuals' choices and then assesses whether demographic characteristics are associated with group membership... It assumes that these subgroups, or latent classes, explain the pattern of responses observed in the data. The Latent class model was estimated with the GMNL package (Sarrias and Daziano 2017) in R studio 2024 (RStudio Team 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 (Dziak et al. 2020). The number of classes to include was informed by the model with the lowest BIC across models with from 2 to 4 classes.

Results

Sample characteristics

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 5.2).

Table 5.2: Respondents characteristics (N=82)

Characteristics	Frequency (N=82, %)
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 Mean (SD) Min, max	 15 (9) (1, 34)
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)
Currently using AI at work	
Yes	44 (54)
No	29 (35)
Don't know	8 (10)

Note: a. The average number of years of experience among "other" professionals (n=6) was 12 (SD 12) range 3-30

DCE Results

The estimation of the mixed logit model yielded significant effects at 1% significance level for all attribute levels (Table 5.3). The estimated standard deviations for six out of nine attribute levels were statistically significant, indicating the presence of unobserved preference heterogeneity in the sample. In contrast, the standard deviations for "improved accuracy of the AI system" and "time saved per patient during treatment planning" were not statistically significant, suggesting no evidence of preference heterogeneity for these attributes.

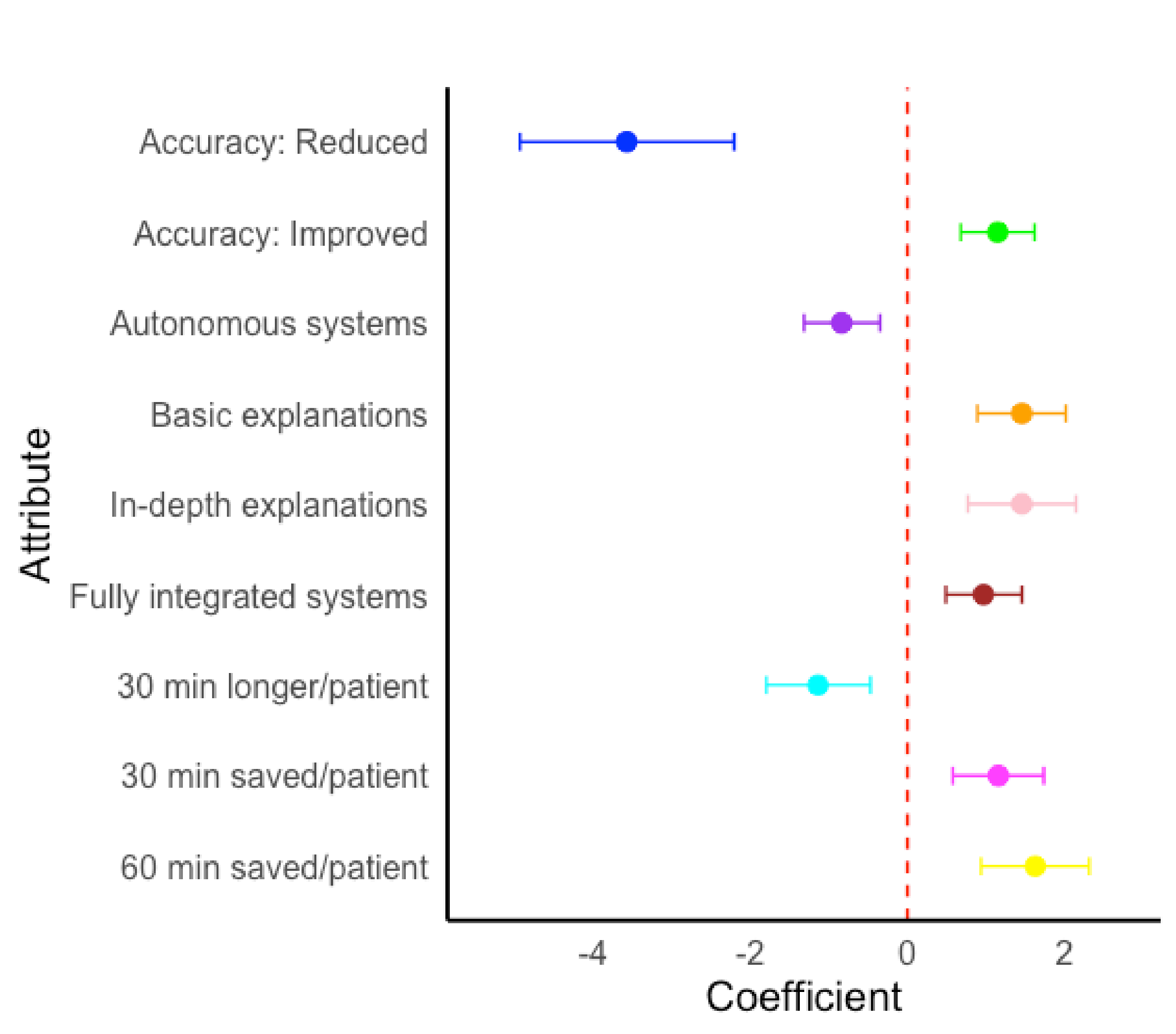
Table 5.3: Results of the DCE responses, analysed using mixed logit model (N=82)

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 (Base =No change)	30 minutes longer	-1.14 (0.34)***	1.36 (0.45)**
	30 minutes saved	1.16 (0.30)***	0.49 (0.73)
	60 minutes 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		

AIC: Akaike information criterion; BIC: Bayesian information criterion; LL: log-likelihood; SD: standard deviation; SE: standard error.
Note: *** p=0, ** p=0.001, * p=0.01, . p=0.05

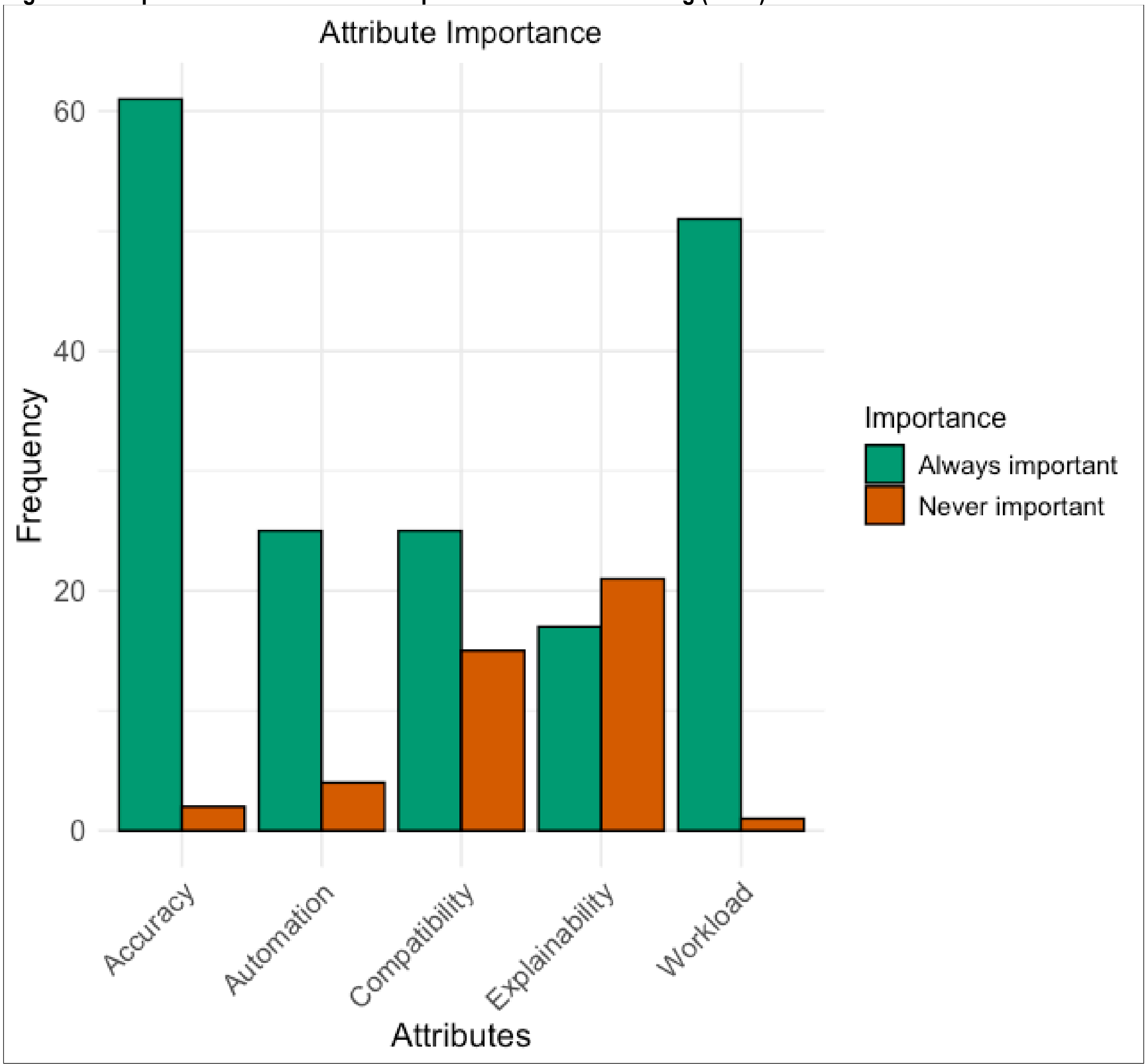
The mixed logit results are also illustrated in Figure 5.2 which shows the point estimate and the corresponding 95% confidence intervals for each attribute level. The results show the highest preference is for an AI-system that reduces workload (time saved), followed by an AI system with an ability to provide explanations (whether basic or in-depth). The results showed that there is a negative utility associated with AI systems with reduced accuracy and with fully autonomous systems.

Figure 5.2: A forest plot of results from DCE (N=82) based on mixed logit model: estimated effect and confidence intervals



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 (Figure 5.3).

Figure 5.3: Importance of attributes in respondents' decision-making (N=82)



The results from LC model are presented in Table 5.4. 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. Preference estimates for the impact on workload for class 2 showed that AI systems that require an additional 30 minutes for treatment plan preparation have statistically significant negative impact on workload. In contrast, time savings of 30 and 60 minutes did not show statistically significant effect for class 2 (Table 5.4).

Table 5.4: Results from a latent class logit model with 2 classes: class specific parameters and model fit statistics (N=82)

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 minutes longer	-0.73 (0.20)***	-0.48 (0.36)***
	30 minutes saved	1.07 (0.23)***	-0.05 (0.33)
	60 minutes 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

AIC: Akaike information criterion; BIC: Bayesian information criterion; LL: log-likelihood; SE: standard error.
Note: *** p=0, ** p=0.001, * p=0.01, . p=0.05

Latent class membership was examined in relation to observable respondent characteristics to support interpretation and potential implementation relevance (Table 5.5). Class assignments were cross tabulated with key respondents’ characteristics, including type of professional role, work settings, years of experience, and prior experience with using AI. Notably, respondents in Class 1, who favoured operational efficiency, were more likely to be radiation therapists and to have longer professional experience.

Table 5.5: Respondents characteristics in the LCA (N=82)

Respondent characteristic	Class 1 (N=62)	Class 2 (N=20)
Professional role (n, %)		
Radiation therapist	36 (59)	7 (35)
Medical physicist	7 (12)	2 (10)
Radiation oncologist	15 (25)	9 (45)
Other[a]	4 (7)	2 (10)
Work settings (n, %)		
Public	47 (78)	14 (70)
Private	4 (7)	3 (15)
Both	10 (17)	3 (15)
Years of experience (n, %)		
1–5	14 (23)	6 (30)
6–15	16 (27)	4 (20)
16–22	16 (27)	7 (35)
23+	15 (25)	3 (15)
Currently using AI at work (n, %)		
Yes	32 (53)	12 (60)
No	23 (38)	6 (30)
Don’t know	6 (10)	2 (10)

AI = artificial intelligence; LCA = latent class analysis

The marginal willingness-to-save (WTS) time values for each attribute level are presented in Table 5.6. 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 minutes compared with a human based system would be required. To compensate for a system that was autonomous, a time saving of 32 minutes 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 minutes. 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 5.6: Willingness-to-save time results (N=82)

Attributes	Levels	Mean, minutes (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)***

SE: standard error; WTS: willingness-to-save
Note: *** p=0, ** p=0.001, * p=0.01, . p=0.05

Additional analyses

Attitudes and opinions

Responses to questions about survey difficulty and respondents' attitudes and opinions about AI are presented in Figure 5.4 and Figure 5.5 . Most respondents found the DCE tasks manageable, with over half disagreeing that the tasks were difficult or that distinguishing between options was challenging, and the majority (87%) reporting they considered all features when making decisions. Regarding attitudes to AI in radiation therapy, most respondents acknowledged the potential for AI-driven bias (69%) but believed AI would improve RT delivery (77%) without significantly diminishing human connection (76%). There was strong support for including information about AI use in informed consent processes (43%), recognition of AI's role in enhancing workforce skills (60%), and agreement that while AI can automate tasks and potentially displace humans (49%), it cannot fully replace human roles (75%).

Figure 5.4:Attitudes and Opinions on AI in RT planning (N=81)

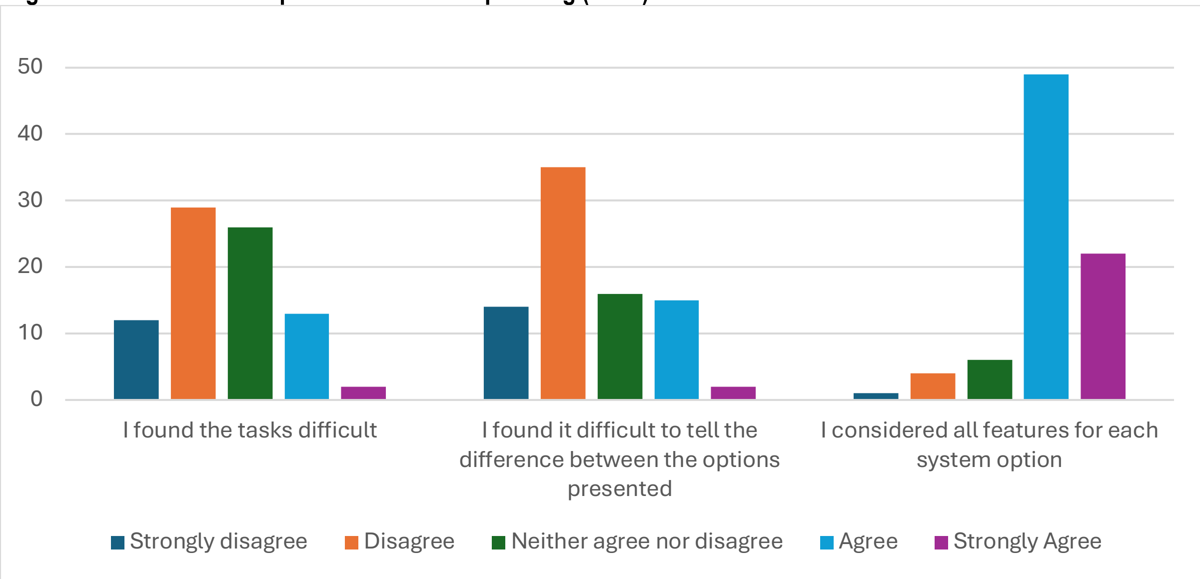
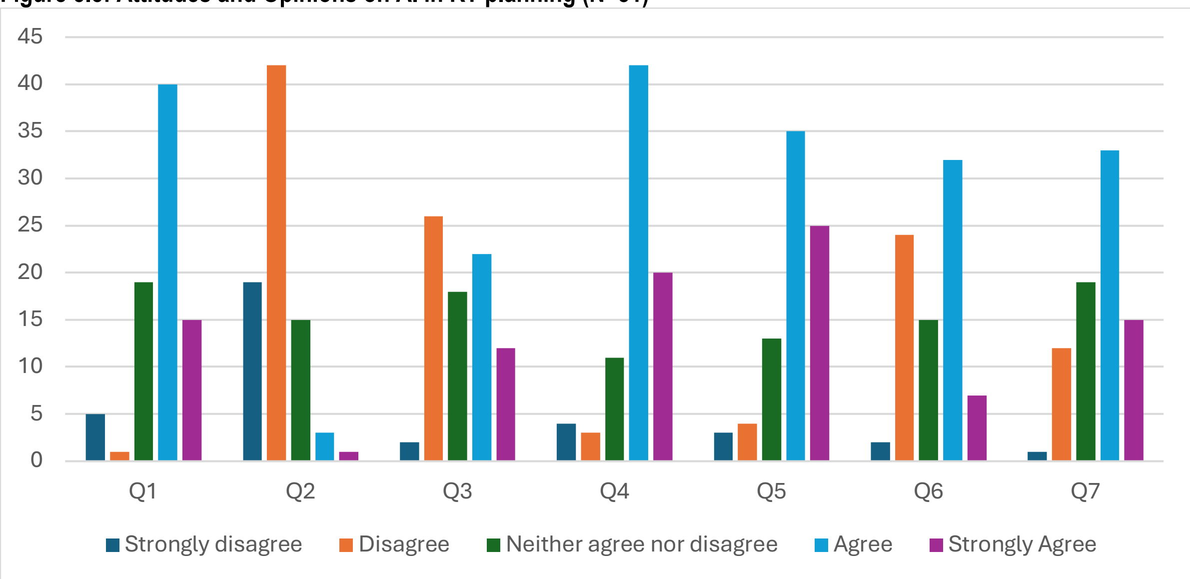


Figure 5.5: Attitudes and Opinions on AI in RT planning (N=81)



AI: artificial intelligence; DCE: discrete choice experiment; RT: radiation therapy

Notes:

Q1. AI algorithms, based on the data they learn from, can develop biases that affect how healthcare is provided to different groups of people

Q2. The implementation of AI in RT treatment planning diminishes human connection in patient care.

Q3. Informed consent for patients should include information about AI use in diagnostic and treatment recommendations

Q4. The use of AI technology will improve the delivery of RT.

Q5. AI technology can never replace the role of humans.

Q6. The increasing use of AI in automating tasks may lead to workforce displacement.

Q7. The use of AI contributes to a more diverse skill set within the team by allowing staff to cultivate specialised expertise.

Sensitivity analyses

The results of a sensitivity analysis after excluding the 17 (22%) of respondents who reported difficulty in distinguishing between the presented options are presented in Table 5.7. The results were consistent with the base case results.

Table 5.7: Results of sensitivity analysis: DCE responses analysed using a mixed logit model, excluding respondents to follow-up question[a] (N=65)

Attributes	Levels	Mean (SE)	SD (SE)
Accuracy (Base = Same as current)	Reduced	-3.81 (0.82)***	2.59 (0.69)***
	Improved	1.26 (0.31)***	0.36 (0.67)
Automation (Base = Assistive)	Autonomous	-1.03 (0.33)**	1.81 (0.43)***
Explainability (Base = “Black box”)	Basic explanations	1.49 (0.35)***	1.11 (0.40)**
	In-depth explanations	1.32 (0.39)***	1.68 (0.52)**
Compatibility (Base = Separate systems)	Fully integrated systems	0.97 (0.29)***	1.24 (0.35)***
Impact on workload (Base =No change)	30 minutes longer	-1.36 (0.43)**	1.34 (0.54)*
	30 minutes saved	1.26 (0.34)***	0.08 (0.81)
	60 minutes saved	1.93 (0.45)***	1.00 (0.51)
Number of draws	5000		
Sample (observations)	792		
BIC	783.71		
AIC	699.57		
LL	-331.78		

AIC: Akaike information criterion; BIC: Bayesian information criterion; LL: log-likelihood; SD: standard deviation; SE: standard error.
Note: *** p=0, ** p=0.001, * p=0.01, . p=0.05

a. Respondents agreed (n=15) or strongly agreed (n=2) with the statement, ‘I found it difficult to differentiate between the options presented”.

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. Given the clinical cancer context, it is expected that accuracy ranked among the most important attributes. This raises the possibility that accuracy attribute could be dominant, potentially limiting the estimation of trade-offs for the remaining attributes. To mitigate this risk, some choice sets were designed with options of equal accuracy, helping to reduce accuracy dominance and encourage consideration of other attributes.

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 (Von Wedel and Hagist 2022). 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 (Debnath 2023).

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 the 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 reach out to a 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 healthcare professionals' 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.

Chapter 6: Preferences for types of artificial intelligence in radiation therapy treatment: A discrete choice experiment with Australian general public.

Publication manuscript details

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Authors contribution: The research question and methodology and the design of the study were developed by ML, DS, JY, SJ and RV. ML oversaw data collection, performed the data analysis and interpretation of results and drafted the manuscript. All co-authors contributed to the interpretation of the results, reviewed the manuscript and approved the final version for submission to a journal.

Publication notes: The work from this Chapter was submitted to the Value in Health Journal, themed section focused on the integration and impact of artificial intelligence (AI) in healthcare. The manuscript is under peer review at the time I submitted this thesis for examination. The chapter presented in this thesis is the version submitted to the journal for publication.

Ethics approval for the DCE was obtained from the University of Technology Sydney Human Research Ethics Committee as part of the CHERE's program ethics (No. 2015000135, Figure A5.1, Appendix 5). Respondent confidentiality was ensured by anonymising the data entry in the survey. All respondents have provided informed consent. Respondents had the right to withdraw from the study at any time and without giving reasons and to request the deletion of the collected data at any time during the survey. Respondents were informed that they could contact the Research Office directly if they had any concerns, they wished to raise independently of the research team. Both a phone number and an email address were provided for this purpose. Researchers' contact information was provided on the first and last page in case the respondents had questions. The respondents could contact the researchers directly by phone or via a contact email address. The respondents were told that the results of this study could be presented at national and international conferences and published in peer-reviewed journals.

Abstract

Objectives:

The integration of artificial intelligence (AI) in radiation therapy offers significant potential to enhance cancer care by improving diagnostic accuracy, streamlining workflows, and reducing treatment delays. However, the adoption of AI in clinical settings depends heavily on its acceptability, shaped by perceptions of accuracy, cost, efficiency, and ethical considerations. This study explores the preferences of the Australian general population regarding the features of AI systems in radiation therapy.

Methods:

A discrete choice experiment (DCE) was conducted with 533 respondents, who were representative of the Australian population in terms of age and gender. Respondents were presented with hypothetical scenarios comparing AI systems described by attributes including accuracy, decision-making autonomy, impact on out-of-pocket costs, treatment timelines, and data privacy. Preferences were analysed using mixed logit and latent class models to evaluate heterogeneity and willingness-to-pay for AI system attributes.

Results:

Respondents preferred AI systems with enhanced accuracy and reduced treatment delays. Systems less likely to misclassify tissues were highly valued, while fully autonomous AI systems were less favoured compared to assistive systems requiring clinician oversight. Data privacy concerns varied, with some respondents prioritizing consent-based data usage. Heterogeneity analysis revealed four distinct preference classes, highlighting trade-offs between cost, speed, and ethical considerations. Willingness-to-pay estimates showed the respondents were willing to pay for features such as enhanced oversight, reduced time burden, and AI-driven data use.

Conclusions:

This study provides important information about Australian general public preferences for AI in treatment planning and can be used to inform future research on economic evaluations and implementation of AI-driven technologies in radiation therapy.

Introduction

Rapid technological innovations in cancer diagnosis and treatment have contributed to an estimated 30% reduction in cancer mortality over the last 20 years (AIHW 2024b). These innovations include advances in genomic and precision medicine, diagnostic imaging and artificial intelligence (AI).

AI involves programming a computer to simulate human reasoning, and decision-making. It can find patterns in large datasets by identifying relationships among data points that cannot be easily perceived by the human brain. In cancer care, AI analyses imaging data and health records to tailor patient care and estimate cancer probabilities. Radiation oncology focuses on radiation therapy for cancer treatment. Imaging has an essential role in radiotherapy planning and delivery. Optimal use of imaging allows higher doses of radiation to be delivered to the tumour, while sparing surrounding tissues (Beaton et al. 2019). The complexity of radiation therapy and the heavy reliance on medical imaging technologies have increased requirements for data collection and analysis, contributing to professional burnout and treatment access challenges (Thompson et al. 2017).

The use of AI in radiation therapy has the potential to optimise the use of medical images and to address challenges including healthcare staff shortages, inefficiency and variation in treatment planning and delivery (Mun and Dieterich 2023). AI enhances radiation therapy treatment by improving tumour detection, segmentation accuracy, and treatment planning (Pinto-Coelho 2023)The use of AI in radiation therapy has the potential to optimise the use of medical images and to address challenges including healthcare staff shortages, inefficiency and variation in treatment planning and delivery (Mun and Dieterich 2023). AI enhances radiation therapy treatment by improving tumour detection, segmentation accuracy, and treatment planning (Pinto-Coelho 2023). Research shows that AI outperforms traditional methods in radiation dose prediction (Zadnorouzi and Abtahi 2024), treatment design, and dose delivery (Cai et al. 2023), creating more efficient and precise treatment plans. The risks related to AI include potential errors in the algorithm or it not functioning as intended, and over-reliance on technology, which can lead to the dehumanisation of patient care (Kolla and Parikh 2024; Mittelstadt et al. 2016). In addition, AI systems can't fully replicate clinician decision-making because they don't integrate patient cognitive status, quality of life, and individual preferences.

Despite the rapid development and the potential benefits of AI technologies for cancer treatment, only a small proportion of available AI-based technologies have been successfully adopted in clinical settings (Ahmed et al. 2023). Challenges related to AI implementation include limited regulatory guidelines, high upfront costs for integration of AI in clinical workflow and existing IT infrastructure, and challenges in AI algorithm explainability and monitoring post deployment.

Human biases can affect how AI algorithms are used in clinical settings. Factors such as the expertise, technological literacy, and age of physicians affect the adoption of these technologies in healthcare (Ahmed et al. 2023). Perceived usefulness, performance expectancy, attitudes, trust, and effort expectancy are predictors of adoption of AI technologies (Kelly et al. 2023). Low user acceptance of AI can waste resources, create surplus unused AI technologies, and potentially hinder technological innovation, ultimately harming consumers (Kelly et al. 2023).

Given the complexity of AI's potential impact on cancer diagnosis, treatment, and care delivery, it is important to understand consumer preferences, both from those of providers and of recipients of care. While the perspectives of healthcare professionals are a critical factor, the acceptability of AI technologies to consumers is also important for their successful adoption in clinical practice. Patients' willingness to accept AI-assisted care depends on factors such as perceived accuracy, transparency, and alignment with their values and expectations (Haan et al. 2019). Research has shown that while patients appreciate AI's potential to enhance diagnostic precision and treatment planning, they also express concerns regarding autonomy, ethical considerations, and the role of human oversight (Prakash et al. 2022). If these concerns are not addressed, resistance to AI-driven healthcare solutions may hinder their widespread adoption, limiting their potential benefits.

For these reasons, in addition to their predictive accuracy and effectiveness, successful AI systems must be evaluated in terms of their broader impact on healthcare systems delivery. This includes considering human factors that influence technology adoption and accounting for the unintended consequences of AI use in medicine. This study aims to investigate the preferences for the adoption of AI technologies in radiation oncology settings from the perspective of the general population as consumers of healthcare services.

Methods

This study involved conducting a DCE to identify the features of AI systems and their impact on radiation therapy delivery that are most important to the general population as consumers of healthcare services. A DCE is a structured survey method that elicits preferences by presenting respondents with a series of hypothetical choice tasks, where each option is characterised by multiple attributes to simulate realistic decision-making scenarios. This method is especially relevant for new healthcare products and technologies, such as AI, for which market data are limited or unavailable for assessing user preferences.

Survey development

The survey instrument was developed using the steps recommended by the Professional Society for Economics and Outcomes Research (ISPOR) taskforce (Bridges et al. 2023). The DCE tasks were created and refined in stages based on both qualitative and quantitative methods, with the qualitative component comprising structured consultation with expert researchers rather than primary qualitative data collection. 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 radiation therapy planning. A summary of the survey structure is presented in Figure A6.3, Appendix 6.

Attributes and levels

Vignettes, attribute descriptions, and levels were developed through a multi-step process involving collaboration with clinical experts specialising in radiation therapy treatment planning and delivery. These experts provided input to ensure that the choice context accurately described a real-world treatment scenario where AI treatment options might be used, and that the treatment options themselves were plausible. Notably, these clinicians are also members of AI special interest groups within their professional networks, which ensured that their insights were informed by both current clinical practice and the evolving role of AI in radiation therapy, while also accounting for differences in perspective between professional and public audiences. In addition, the study incorporated findings from a published literature review (Table A6.1, Appendix 6) and consultation with an expert group of DCE researchers at University of Technology Sydney (Centre for Health Economic Research and Evaluation) to enhance methodological rigor.

The attributes of AI systems that were included in the experiment are described in Table 6.1. These attributes encompass “accuracy compared with clinicians”, use of AI in “diagnosis and treatment oversight”, “AI impact on out-of-pocket costs”, “AI impact in time to cancer treatment”, and “AI-driven use of your data” Table 6.1

The process of defining attributes and levels involved adapting the framework developed in Chapter 5 while making deliberate modifications to reflect the different decision contexts and respondent groups. Whereas the earlier study focused on healthcare professionals, the current DCE targets the general public, necessitating changes to ensure attributes were meaningful, interpretable, and relevant to lay respondents. To ensure clarity and accuracy, feedback from a convenience sample of the general population was gathered. As a result, some attributes were reformulated or replaced to better capture outcomes and trade-offs that are salient to the general public, for example, framing time impacts in terms of time to cancer treatment rather than time in clinic, and explicitly including the use of patient data as an attribute reflecting public concerns about data use and governance. These differences were intentional and designed to accommodate variation in stakeholder perspectives rather than to replicate the attribute set presented in Chapter 5 directly.

Table 6.1: Overview of attributes and levels

Attributes	Levels	Definition
Accuracy compared with clinicians	1. The AI system sometimes misses cancer 2. The AI never misses cancer but sometimes calls normal tissue cancer 3. The AI system is the same as clinicians at identifying cancer correctly 4. The AI system is less likely to miss cancer and less likely to call healthy tissue for cancer	The ability of the AI-systems to correctly identify cancerous or healthy tissues in medical images such as X-rays
Diagnosis and treatment oversight	**1.** Assistive: The AI-system is used as a decision support tool; it provides doctors with suggestions based on your initial test results, but doctors still oversee and approve the treatment recommendations **2.** Fully autonomous: The AI system plans and delivers radiation therapy based on your test results all by itself, without needing doctors to step in during the process	The extent to which the AI system makes decisions about treatment or assists clinicians in their decisions.
AI impact on out-of-pocket costs[a]	1. No additional costs ($0) 2. Additional $35 3. Additional $50 4. Additional $100	The out-of-pocket costs associated with each visit
AI impact on time to cancer treatment Compared to the usual 30 days waiting time at treatment centre not using AI it will be[b]	1. 10 days longer 2. No change (30 days) 3. 10 days shorter 4. 15 days shorter	The impact of AI system adoption on the time needed to start cancer treatment
AI-driven use of your data to update its learning/model	1. The AI may use your medical images only, and only with your consent 2. The AI uses your medical images only, without needing your consent 3. The AI system may use your medical images and health record data only with your consent 4. The AI uses your medical images and your health record data without needing your consent	How AI is using your data such as medical images and health record data to improve its working/performance

Notes: Selection of the attribute levels was informed by

a. the average out of pocket payment in Australia of $69.78 (van Gool et al. 2023)

b. the estimated waiting times for radiotherapy in Australia 2018-2019 (Australian Institute of Health and Welfare 2020)

An example choice task from the DCE is shown in Figure 6.1. Each choice task presents a vignette in which respondents were asked to imagine undergoing radiation therapy facilitated by various AI-systems. Respondents were asked to select their preferred option based on the attributes of AI -systems provided. The primary focus of the study was on understanding preferences between different AI-based approaches. After selecting their preferred AI system, respondents were then asked if they would prefer the treatment centre using the AI system they chose or a treatment centre that does not use AI. This opt-out option was included to reflect the realistic options for patients in clinical practice and to understand overall attitudes to AI, rather than serving as a third equivalent choice in the main comparison.

Figure 6.1: Example DCE choice task

Imagine that you were recently diagnosed with cancer, and you will be treated with radiation therapy treatment. You have a choic between two treatment centres. AI-systems are used for diagnosis and treatment at both treatment centres, but the systems are different. Which treatment centre would you prefer?

Please click on the treatment centre you prefer. Please hover your mouse or pointer over the highlighted words if you want to see more information about those terms.

	Treatment centre A	**Treatment centre B**
Accuracy Compared with clinicians	The AI system is less likely to miss cancer and less likely to call healthy tissue for cancer	The AI system sometimes misses cancer
Diagnosis and treatment oversight	**Assistive**	**Fully autonomous**
AI impact on out-of-pocket costs	Additional $35	Additional $50
AI impact on time to cancer treatment Compared to the usual 30 days waiting time at treatment centre not using AI it will be	15 days shorter	10 days longer
AI-driven use of your data to update its learning/model	The AI may use you medical images only, and only with your consent	The AI uses your medical images only, without needing your consent
Which treatment centre do you prefer?	◉	○

Compared with the treatment centre you have chosen, would you prefer a treatment centre that does not use AI?

Please select one response.

Yes

No

Designed experiment

The designed experiment, constructed in R (R Core Team 2024) using the idefix package (Traets et al. 2020), contained 256 choice tasks divided into 16 versions, each with 16 choice tasks. The design was constructed to allow for the estimation of the main effect using a multinomial logit (MNL) model and used an uninformative prior. To evaluate the ability the design (i.e. design that maximised the precision of estimated choice-model parameters for a given number of choice questions (Johnson et al. 2013), several simulations were conducted in R, and in all cases the assumed priors were recovered accurately. . The questionnaire and DCE were piloted with a general population (n=50) during a survey soft launch to assess comprehension and to ensure the DCE was performing as intended. Following the DCE choice tasks, the respondents were prompted to rate the perceived difficulty of the choice task using a 5-level Likert scale, ranging from “strongly agree" to "strongly disagree." This rating aimed to assess task comprehension and the overall survey difficulty. In our open-ended question no attributes were consistently listed as being missing.

Data collection

The survey was administered by Pure Profile, an online panel provider with over 1 million panel members. Panel members who were aged 18 year and older, living in Australia and able to speak and read English, were invited to participate via an email link which granted access to the survey. Respondents were recruited to be representative of the general population of Australia by age and gender. Panel members were asked indicate consent at the end of the introduction which contained information about the content and purpose of the study, and they could exit the survey at any point. Data were collected between and 26 June and 28 June 2024. This study was approved by the University of Technology Health Research Ethics Committee, 3 May 2024 (UTS HREC REF NO. 2015000135, Figure A6.2, Appendix 6).

Data analysis

Descriptive statistics were used to summarise the characteristics of the overall sample. A multinomial logit model (MNL) was originally fitted to the choice data. The probit model was used to analyse the data from the opt-out responses and to allow modelling of the choice as being driven by an underlying utility influenced by the attributes of the AI systems and individual-specific characteristics. The respondents, after choosing between two main options (Treatment centre A and Treatment centre B) could indicate a preference for an opt out which corresponded to choosing a treatment centre that does not use AI.

The marginal willingness to pay was estimated using coefficients from the MNL logit model using the AI impact on out-of-pocket cost variable to calculate a marginal rate of substitution (MRS), which provide information on the rate at which respondents are willing to trade the level of one attribute for a preferred level of another attribute (Mott et al. 2020). Relative attribute importance was calculated by dividing the range of marginal utilities of the given attribute by the sum of all attribute ranges. The estimation was based on a piece-wise linear approach described in Johnson et al. (2011). This method derives cost values from dummy-coded utility estimates, assuming linear interpolation between discrete cost-utility points. The cost attribute was specified at four levels: 0, 35, 50, and 100 AUD, forming the basis for constructing linear segments between adjacent cost levels. To capture non-linear marginal utility of cost, the cost attribute was effects-coded, while other attributes (i.e. accuracy, diagnostic and treatment oversight, time impact, and AI-driven data use) were dummy-coded. In addition, the "AI-driven use of data" attribute was recoded to allow separate estimation of preferences for "use of health data" and "consent". The slope of each linear segment was calculated between two cost levels and their corresponding utility coefficients. WTP values for each attribute level were then estimated by identifying the relevant cost segment into which the utility difference fell and applying linear interpolation. This approach allows for estimation of WTP by accommodating non-linearities in the cost-utility relationship.

Two approaches were used to account for heterogeneity: mixed logit (MIXL) and latent class (LC) modelling. Mixed logit modelling generalises the MNL model by leveraging variation in choices across respondents to estimate variation in preferences in the population (Sarrias and Daziano 2017). Each model was estimated by maximum simulated likelihood, with varying numbers of Halton draws, ranging from 100 to 5000 Preferences for attribute levels were estimates relative to the base (omitted) level. Another approach to explore preference heterogeneity in the data is to use a latent class (LC) model (Ryan et al. 2008). Latent class analysis is used to identify subgroups within a population according to individuals' choices and then assesses whether demographic characteristics are associated with group membership. It assumes that these subgroups, or LCs, explain the pattern of responses observed in the data and that preference heterogeneity follows a discrete distribution for the attribute levels. The specific characteristics that are likely to impact on preferences were identified. To evaluate model fit, log likelihood, Akaike information Criterion (AIC) and Bayesian Information Criterion (BIC) were determined (Dziak et al. 2020). The number of classes to include was determined by the model with the lowest AIC and BIC across models with from 2 to 6 classes. In addition, the choice of best model fit was informed by an assessment of the average (over respondents) of the highest posterior probability of class membership and the assessment of the model's ability to make in-sample predictions of the actual choice outcomes by classifying the respondent as a member of a class "c" if class "c" gives him or her highest posterior membership probability. For each subsample of such respondents, the probability of the actual choice was predicted, and the probability of the choice conditional on being in class "c" (Newton et al. 2013). The statistical data analysis was conducted in R Studio (RStudio Team 2024) using GMNL package (Sarrias and Daziano 2017).

Results

Sample characteristics

A total of 533 respondents completed the survey. Most were born in Australia (n=449, 84%), with 72 (14%) born overseas, primarily in Europe (Table A6.2, Appendix 6), with a small proportion identifying as Aboriginal (n=8, 2%) (Table 6.2). Respondents' ages were well-distributed across age groups, with most being between 25 and 44 years (n=192, 36%). Most held a bachelor's degree (n=176, 33%) and were employed full-time (n=247, 46%) or part-time (n=124, 23%). Forty-three percent (n=230) reported being in "good health or better", 59% (n=312) felt knowledgeable about cancer, or knew someone diagnosed with cancer (n=410, 77%). The study population was representative of the broader Australian population in demographic and education.

Table 6.2: Respondents characteristics (N=533)

Characteristics	All respondents N=533 (n, %)	Australian population[a] (%)
Gender[a]		
Female	275 (52)	51
Male	258 (48)	49
Country of birth[a]		
Australia	449 (84)	71
NZ	11 (2)	29
Other	72 (14)	
Prefer not to say	1 (<1)	
Aboriginal status[b]		
Aboriginal	8 (2)	3
Torres Strait Islander	3 (1)	<1
Both	2 (<1)	<1
Neither	516 (97)	NA
Prefer not to say	4 (1)	NA
Age[a]		
18-24 years	60 (11)	7[j]
25-34 years	98 (18)	15
35-44 years	94 (18)	14
45-54 years	86 (16)	12
55-64 years	75 (14)	11
65-74 years	81 (15)	9
75+ years	39 (7)	8
Education[c]		
Post graduate degree (master's or Doctorate)	61 (11)	12
Bachelor's/honours degree	176 (33)	20
Diploma/advanced diploma	71 (13)	10
Certificate	75 (14)	17
Year 12 or equivalent	89 (17)	18
Year 11 and below	60 (11)	21
Did not go to school	1 (<1)	NA
Employment[d]		

Characteristics	All respondents N=533 (n, %)	Australian population[a] (%)
Employed (full-time)	247 (46)	69
Employed (part-time)	124 (23)	31
Home duties	25 (5)	NR
Not employed but looking for a job	18 (3)	NR
Not-working student	5 (1)	NR
Other (specify)[e]	4 (1)	NR
Retired	110 (21)	16
Health state (self-assessed) [f]		National Health Survey[f]
Excellent	58 (11)	19
Very good	160 (30)	36
Good	230 (43)	29
Fair	77 (14)	12
Poor	8 (2)	4
Cancer[g]		
I don't know	13 (2)	NA
No	445 (83)	NA
Prefer not to say	3 (1)	NA
Yes	72 (14)	NA
Cancer_others[h]		
I don't know	7 (1)	NA
No	111 (21)	NA
Prefer not to say	5 (1)	NA
Yes	410 (77)	NA
Cancer knowledge[i]		
No	221 (41)	NA
Yes	312 (59)	NA

ABS = Australian Bureau of Statistics; NR: not reported
Notes:

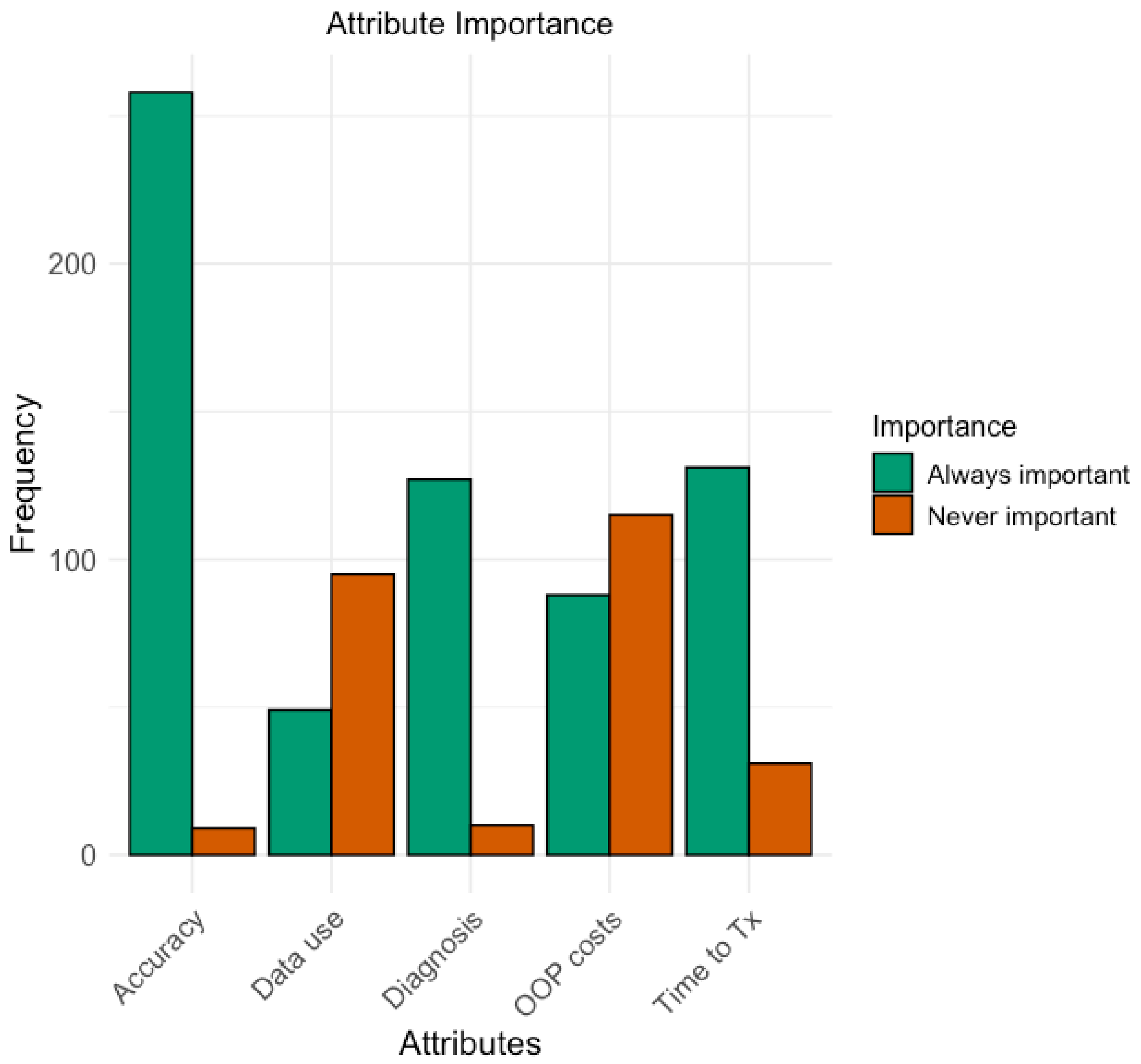
a. ABS, https://www.abs.gov.au/statistics/people/population/births-australia/2022#national, accessed 11 Nov 2024
b. ABS,https://www.abs.gov.au/statistics/people/aboriginal-and-torres-strait-islander-peoples/aboriginal-and-torres-strait-islander-people-census/latest-release
c. ABS, https://www.abs.gov.au/statistics/people/education/education-and-work-australia/latest-release#data-downloads
d. ABS, https://www.abs.gov.au/statistics/labour/employment-and-unemployment/labour-force-australia/oct-2024#employment
e. Disabled (n=1), Planned break from work force (n=1), Self Employed part time (n=1), Student who works as a casual (n=1)
f. National Health Survey 2022: https://www.abs.gov.au/statistics/health/health-conditions-and-risks/national-health-survey/latest-release#about-the-national-health-survey, accessed 11 November 2024
g. Have you ever been told by a doctor or nurse that you have any type of cancer?
h. Has someone you know well ever been told by a doctor or nurse that they have any type of cancer?
i. Do you feel knowledgeable about cancer treatment and what it entails?
j. ABS data Reported for age 20-24

DCE Results

Mixed logit analysis

The results from the mixed logit analysis are presented in Table 6.3. The estimation of the mixed logit model yielded significant effects at the 1% significance level for all levels of all attributes, except AI-driven use of medical images and health record data and the impact of AI on cancer treatment timelines that lead to a 10-day increase in the time to treatment. The results showed negative utility associated with fully autonomous AI systems that had the highest impact on out-of-pocket costs and AI systems that resulted in longer time to treatment. The results show the highest preference is for an AI system with improved accuracy described as being less likely to miss cancer and less likely to classify healthy tissue as cancer, followed by an AI-system that offers reduction in time to cancer treatment (Table 6.3). The results from the DCE were consistent with the responses to questions about attribute importance that revealed that AI accuracy and AI impact on time to treatment were the most frequently considered attributes when choosing between the AI systems (Figure 6.2).

Figure 6.2: Attribute importance (N=533)



OPP= out-of-pocket, Tx= treatment;

Table 6.3 also presents the estimated standard deviations for each attribute. The estimated standard deviations for nine out of 12 attribute levels were statistically significant, indicating that there is preference heterogeneity in the sample. The standard deviations for “AI impact on out-of-pocket cost of $100”, “AI impact on time to cancer treatment that led to 10 days shorter time”, and “AI use of health record data”) were not statistically significant.

Table 6.3: Results of the DCE responses, analysed using mixed logit model (N=533)

Attributes	Levels	Mean (SE)	SD (SE)
Accuracy (Base = Same as clinician)	The AI system sometimes misses cancer	1.29 (0.09) ***	1.25 (0.1) ***
	AI never misses cancer but sometimes calls normal tissue cancer	1.66 (0.1) ***	1.09 (0.1) ***
	The AI system is less likely to miss cancer and less likely to call healthy tissue for cancer	1.99 (0.1) ***	1.06 (0.1) ***
Diagnosis and treatment oversight (Base = Assistive)	Autonomous	-0.36 (0.06) ***	0.82 (0.06) ***
AI impact in OOP (Base = No additional costs: $0)	Additional $35	0.5 (0.06) ***	0.8 (0.06) ***
	Additional $50	0.21 (0.05) ***	0.34 (0.07) ***
	Additional $100	-0.18 (0.04) ***	0.08 (0.16)
AI impact on time to treatment (Base = No change: 30 days)	10 days longer	-0.14 (0.08) .	0.95 (0.09) ***
	10 days shorter	0.67 (0.07) ***	0.03 (0.23)
	15 days shorter	0.75 (0.08) ***	0.58 (0.11) ***
AI-driven use of your data (Base = No health record data)	Includes health record data	-0.06 (0.05)	0.25 (0.14) .
AI-driven use of your data (Base = No consent required)	Consent required	0.4 (0.06) ***	0.75 (0.07) ***
Number of draws			5000
Sample (observations)			8528
BIC			9945.561
AIC			9776.334
LL			-4864.2

AIC: Akaike information criterion; BIC: Bayesian information criterion; LL: log-likelihood; OPP: out-of-pocket payment; SD: standard deviation; SE: standard error.
Note: *** p=0, ** p=0.001, * p=0.01, . p=0.05

The mixed logit results are also illustrated in Figure 6.3, 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 with improved accuracy described as being less likely to miss cancer and less likely to classify healthy tissue as cancer, followed by an AI system that offers reduction in time to cancer treatment.

Figure 6.3: Mixed logit model results (N=533)

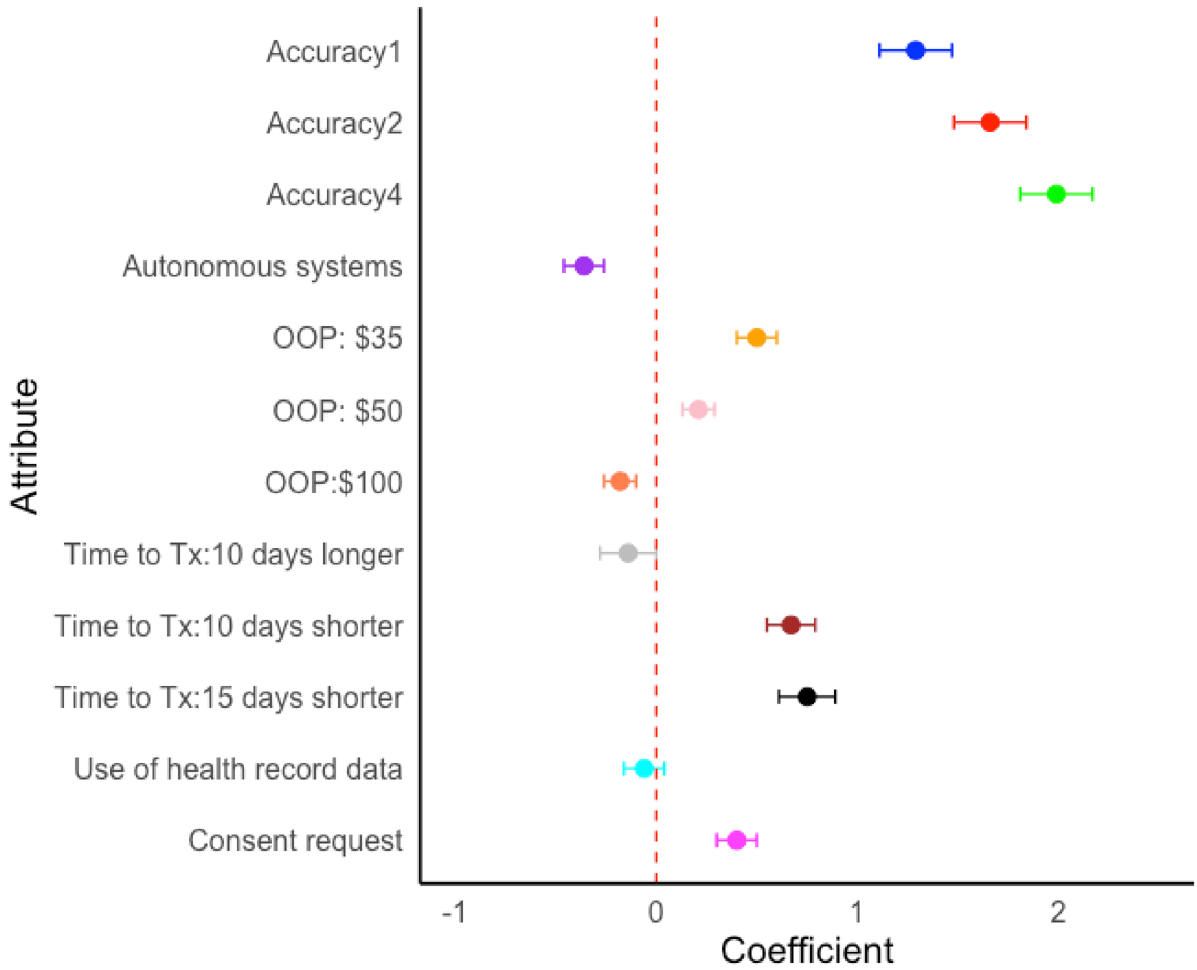


Figure legend: The round marks indicate the coefficient estimates from the mixed logit model with their 95% confidence intervals for the attribute levels (y-axis). The x-axis represents the coefficient values, with a red dashed vertical line indicating the zero-reference point. Positive coefficients indicate a preference for the attribute level, while negative coefficients indicate a disfavour.

Latent class analysis

The results from LC analysis are presented in Table 6.5. Based on the BIC estimates and the assessment of posterior average class probability and respondents class membership the best fit was the model with four classes (Table 6.4).

Table 6.4: Models goodness of fit statistics (N=533)

Classes	Parameters, N	Log-Likelihood	AIC	BIC
2	8528	-5038.2	10126.47	10302.75
3	8528	-4912.4	9900.859	10168.8
4	8528	-4829.8	9761.558	10121.16
5	8528	-4723.4	9574.855	10026.13
6	8528	-4689.2	9532.398	10075.33

AIC: Akaike information criterion; BIC: Bayesian information criterion

The latent class analysis identified four distinct subgroups of respondents (Classes 1 shared 7.2%, Class 2 shared 38.5%, Class 3 shared 45.5% and Class 4 shared 8.8%) with varying preferences for AI systems in radiation therapy. All classes showed positive preference for AI systems with improved accuracy and AI systems that reduce time to treatment. All classed showed negative preference for AI systems having full autonomy. Respondents in Class 3 (45.5% share) and Class 4 (8.8% share) had negative preference for AI systems that increased out-of-pocket costs. The negative coefficient associated with the highest out-of-pocket cost ($100) in Class 4 suggests that this segment of respondents may be highly cost-sensitive or, alternatively, present a protest response to the inclusion of cost in the choice task. This interpretation is plausible given the Australian public healthcare context, in which radiation therapy is typically provided free of charge or subsidised. Respondents in Class 2 (38.5% share) and Class 3 were sensitive to privacy concerns regarding AI use of medical data without consent. These results show substantial heterogeneity in patient preferences, influenced by trade-offs between accuracy, autonomy, cost, treatment speed, and data privacy in AI-enabled healthcare systems.

Table 6.5: Latent class logit results: model with 4 classes (N=533)

Attributes	Levels	Class 1 (Coeff, SE)	Class 2 (Coeff, SE)	Class 3 (Coeff, SE)	Class 4 (Coeff, SE)
Accuracy (Base = Same as clinician)	The AI system sometimes misses cancer	0.42 (0.33)	2.69 (0.39) ***	0.17 (0.1) .	0.03 (0.29)
	AI never misses cancer but sometimes calls normal tissue cancer	1.36 (0.34) ***	2.65 (0.34) ***	0.61 (0.13) ***	0.3 (0.32)
	The AI system is less likely to miss cancer and less likely to call healthy tissue for cancer	1.66 (0.38) ***	3.35 (0.38) ***	0.63 (0.11) ***	0.59 (0.28) *
Diagnosis and treatment oversight (Base = Assistive)	Autonomous	-3 (0.36) ***	-0.14 (0.07) .	-0.11 (0.05) *	-0.17 (0.17)
AI impact in OOP (Base = No additional costs: $0)	Additional $35	-0.09 (0.18)	0.33 (0.08) ***	0.15 (0.05) **	3.5 (0.44) ***
	Additional $50	0.52 (0.2) **	0.1 (0.08)	0.08 (0.05)	1.11 (0.25) ***
	Additional $100	-0.03 (0.2)	-0.07 (0.07)	-0.1 (0.05) *	-1.02 (0.26) ***
AI impact on time to treatment (Base = No change: 30 days)	10 days longer	-0.04 (0.4)	-0.2 (0.12) .	0.06 (0.09)	-0.45 (0.29)
	10 days shorter	0.81 (0.3) **	0.79 (0.11) ***	0.4 (0.09) ***	0.31 (0.28)
	15 days shorter	1.34 (0.35) ***	0.95 (0.13) ***	0.28 (0.11) **	0.6 (0.27) *
AI-driven use of your data (Base = No health record data)	Includes health record data	-0.1 (0.25)	-0.17 (0.08) *	-0.01 (0.06)	0.38 (0.2) .
AI-driven use of your data	Consent required	0.49 (0.29) .	0.24 (0.09) **	0.37 (0.06) ***	0.22 (0.18)

Attributes	Levels	Class 1 (Coeff, SE)	Class 2 (Coeff, SE)	Class 3 (Coeff, SE)	Class 4 (Coeff, SE)
(Base = No consent required)					
Average class share		7.2	38.5	45.5	8.8
Constant, SE		Base class	1.68 (0.06) ***	1.85 (0.07) ***	0.21 (0.07) **
Observations					8528
LL					-4829.8
AIC					9761.558
BIC					10121.16

Notes: p-value: *** p=0, ** p=0.001, * p=0.01, . p=0.05

Latent class membership was examined in relation to observable respondent characteristics to support interpretation and potential implementation relevance. Class assignments were cross tabulated with key demographic and experiential variables, including age group, education level, prior cancer experience, and self-reported knowledge about cancer. Distinct patterns were observed across classes. Notably, the privacy-sensitive classes (Classes 2 and 3) had the lowest proportion of respondents with higher educational attainment (Table 6.7), providing insight into the sociodemographic profiles associated with differing preference structures.

Table 6.6: Respondents characteristics in the LCA

Respondent characteristic	Class 1 (N=39)	Class 2 (N=210)	Class 3 (N=236)	Class 4 (N=48)
Age (n, %)				
18-24	8 (21)	23 (11)	27 (11)	2 (4)
25-34	6 (15)	42 (20)	40 (17)	10 (21)
35-44	7 (18)	30 (14)	46 (19)	11 (23)
45-54	5 (13)	37 (18)	36 (15)	8 (17)
55-64	5 (13)	34 (16)	31 (13)	5 (10)
65-74	6 (15)	29 (14)	38 (16)	8 (17)
75+	2 (5)	15 (7)	18 (8)	4 (8)
Education (n, %)				
Year 11 and below	0 (0)	0 (0)	1 (0)	0 (0)
Year 12 or equivalent	4 (10)	28 (13)	28 (12)	0 (0)
Certificate (any level including trade certificate)	6 (15)	34 (16)	37 (16)	12 (25)
Diploma/advanced diploma	5 (13)	33 (16)	33 (14)	4 (8)
Bachelors on honours degree	3 (8)	27 (13)	34 (14)	7 (15)
Post graduate degree (Masters or Doctorate)	15 (38)	63 (30)	79 (33)	19 (40)
Experienced cancer (n, %)				
Yes	4 (10)	28 (13)	32 (14)	8 (17)
No	34 (87)	178 (85)	195 (83)	38 (79)
I don't know	0 (0)	4 (2)	7 (3)	2 (4)
Prefer not to say	1 (3)	0 (0)	2 (1)	0 (0)
Know someone with cancer (n, %)				
Yes	34 (87)	150 (71)	187 (79)	39 (81)
No	5 (13)	53 (25)	44 (19)	9 (19)
I don't know	0 (0)	5 (2)	2 (1)	0 (0)
Prefer not to say	0 (0)	2 (1)	3 (1)	0 (0)
Knowledgeable about cancer treatment (n, %)				
Yes	28 (72)	131 (62)	131 (56)	22 (46)
No	11 (28)	79 (38)	105 (44)	26 (54)

Willingness to pay

The marginal willingness-to-pay (WTP) values for each attribute level are presented in Table 6.7. These reflect the cost that respondents would be willing to pay to compensate for different features of the AI system. The results showed the respondents were willing to pay features such as enhanced oversight, reduced time burden, and AI-driven data use. Autonomous AI systems, which operate independently without clinician oversight, were valued at $79 more than assistive systems, indicating some trust or preference for autonomy in decision-making. Regarding AI-driven use of data, respondents were willing to pay $2 more for systems that require explicit consent, and $45 more for a system that used health record data. AI systems that resulted in 10 days longer to delivered treatment were valued at $45. However, the results were not statistically significant. For some changes in attribute levels (i.e. AI impact on accuracy and reduction in time to treatment), the WTP could not be reliably estimated. This is likely due to estimating WTP in those cases would have required extrapolating beyond the available cost levels included in the DCE. Such extrapolation was not supported by the piecewise linear method (Johnson et al. 2011).

Table 6.7: Willingness-To-Pay results (N=533)

Attributes	Levels	MNL, MEAN (SE)	WTP ($)
Accuracy (Base = Same as clinician)	The AI system sometimes misses cancer	0.85 (0.05) ***	NE
	AI never misses cancer but sometimes calls normal tissue cancer	1.1 (0.05) ***	NE
	The AI system is less likely to miss cancer and less likely to call healthy tissue for cancer	1.32 (0.05) ***	NE
Diagnosis and treatment oversight (Base = Assistive)	Autonomous	-0.24 (0.03) ***	79
AI impact on time to treatment (Base = No change: 30 days)	10 days longer	-0.04 (0.05)	45
	10 days shorter	0.47 (0.05) ***	NE
	15 days shorter	0.5 (0.05) ***	NE
AI-driven use of your data (Base = No health record data)	Includes health record data	-0.02 (0.05)	45
AI-driven use of your data (Base = No consent required)	Consent required	0.29 (0.05) ***	2
OOP COST	$0	0.3 (0.03) ***	
	$35	0.15 (0.03) ***	
	$50	-0.12 (0.03) ***	
	$100	0.3 (0.03) ***	

AI = artificial intelligence; SE: standard error. DS= standard deviation, OOP= out of pocket costs
Note: *** p=0, ** p=0.001, * p=0.01, . p=0.05

Opt-out preferences: probit model

The probit model was used to analyse the data from the opt-out responses. The respondents, after choosing between two main options (treatment centre A and treatment centre B) could indicate a preference for an opt out which corresponded to staying with a treatment centre that does not use AI. The probit model estimates, reveals that accuracy is the dominant factor in people's decisions to opt out of AI-assisted care. Respondents' preferences for AI system accuracy indicate a sensitivity to errors. Compared with an AI system performing at the same level as clinicians, reduction in accuracy was associated with lower preference. In particular, systems that sometimes-missed cancer or misclassifying healthy tissue were less preferred. The results showed that respondents had negative preference for AI systems that were less likely to miss cancer and less likely to call healthy tissue cancer.

This may reflect perceived complexity or scepticism about the claim, suggesting that respondents may be cautious about AI systems that deviate from standard clinical performance, even if it is technically more precise. It is also important to acknowledge that his qualitative and relative approach may over-simplify the nuanced nature of diagnostic performance, particularly in relation to false positives and false negatives, in a way that may not unambiguously situate artificial intelligence (AI) performance relative to clinicians across all levels.

Other attributes, including oversight, time to treatment, and how the AI system uses personal medical data—did not significantly influence preferences (Table 6.8). The positive intercept (0.26) indicates that If the AI system has the baseline characteristics (same accuracy as clinicians, assistive, no extra cost, no time change, no data use), the model predicts that the likelihood of choosing the system is more than 50%.

Table 6.8: Probit model results (N=533)

Attribute	Level	Estimate (SE)
Intercept		0.26 (0.06) ***
Accuracy (Base = same as clinicians)	The AI system sometimes misses cancer	-0.27 (0.05) ***
	The AI never misses cancer but sometimes calls normal tissue cancer	-0.19 (0.05) ***
	The AI system is less likely to miss cancer and less likely to call healthy tissue for cancer	-0.37 (0.05) ***
Diagnosis and treatment oversight (Base = Assistive)	Fully autonomous	0.04 (0.03)
AI impact on out-of-pocket costs (Base = No additional costs ($0)	Additional $35	0.04 (0.03)
	Additional $50	0.03 (0.03)
	Additional $100	-0.06 (0.03) *
AI impact on time to cancer treatment (Base =No change (30 days))	10 days longer	0.08 (0.05) .
	10 days shorter	-0.03 (0.04)
	15 days shorter	-0.06 (0.04)
AI-driven use of your data (Base = No health record data)	Includes health record data	0.03 (0.05)
AI-driven use of your data (Base = No consent required)	Consent required	0.06 (0.04)
Observations	8528	
LL		
AIC		
BIC		

AIC: Akaike information criterion; BIC: Bayesian information criterion; LL: log-likelihood; SE: standard error.
Note: *** p=0, ** p=0.001, * p=0.01, . p=0.05

Subgroup analyses

The results of subgroup analyses showed the preferences were consistent across gender (Table 6.9), with some variation in preferences across different age groups (Table 6.10) and education level (Table 6.11).

Table 6.9: MNL model: subgroup analyses by gender

		Male	Female
Attribute	**Level**	**Estimate (SE)**	**Estimate (SE)**
Accuracy (Base = same as clinicians)	The AI system sometimes misses cancer	0.68 (0.07) ***	1.03 (0.07) ***
	The AI never misses cancer but sometimes calls normal tissue cancer	0.92 (0.07) ***	1.29 (0.07) ***
	The AI system is less likely to miss cancer and less likely to call healthy tissue for cancer	1.13 (0.07) ***	1.52 (0.08) ***
Diagnosis and treatment oversight (Base = Assistive)	Fully autonomous	-0.19 (0.04) ***	-0.3 (0.04) ***
AI impact on time to cancer treatment (Base =No change (30 days))	10 days longer	0.05 (0.07)	-0.12 (0.07) .
	10 days shorter	0.48 (0.07) ***	0.47 (0.07) ***
	15 days shorter	0.46 (0.07) ***	0.56 (0.07) ***
AI-driven use of your data (Base = No health record data)	Includes health record data	-0.05 (0.07)	0.01 (0.07)
AI-driven use of your data (Base = No consent required)	Consent required	0.2 (0.07) **	0.39 (0.07) ***
AI impact on out-of-pocket costs (Base = No additional costs ($0)	Additional $35	0.32 (0.04) ***	0.28 (0.04) ***
	Additional $50	0.18 (0.04) ***	0.12 (0.05) **
	Additional $100	-0.11 (0.04) **	-0.14 (0.04) ***
Observations	4128		4400
LL	-2568.4		-2587.7
AIC	5162.833		5201.319
BIC	5245.065		5284.381

AIC: Akaike information criterion; BIC: Bayesian information criterion; LL: log-likelihood; SE: standard error.
Note: *** p=0, ** p=0.001, * p=0.01, . p=0.05

Table 6.10: MNL model: subgroup analyses by age

		18-24	25-34	35-44	45-54	55-64	65-74	75+
Attribute	**Level**	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**
Accuracy (Base = same as clinicians)	The AI system sometimes misses cancer	0.81 (0.14) ***	0.84 (0.11) ***	0.7 (0.11) ***	0.96 (0.12) ***	0.74 (0.13) ***	1.03 (0.13) ***	1.24 (0.2) ***
	The AI never misses cancer but sometimes calls normal tissue cancer	1.04 (0.15) ***	0.88 (0.11) ***	0.84 (0.11) ***	1.2 (0.13) ***	1.41 (0.14) ***	1.28 (0.14) ***	1.56 (0.2) ***
	The AI system is less likely to miss cancer and less likely to call healthy tissue for cancer	1.09 (0.15) ***	1.19 (0.12) ***	1.01 (0.12) ***	1.47 (0.13) ***	1.47 (0.14) ***	1.6 (0.14) ***	1.93 (0.21) ***
Diagnosis and treatment oversight (Base = Assistive)	Fully autonomous	-0.18 (0.08) *	-0.12 (0.07) *	-0.21 (0.07) ***	-0.27 (0.07) ***	-0.37 (0.08) ***	-0.35 (0.08) ***	-0.34 (0.11) **

		18-24	25-34	35-44	45-54	55-64	65-74	75+
Attribute	**Level**	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**
AI impact on time to cancer treatment (Base =No change (30 days))	10 days longer	-0.23 (0.14) .	-0.17 (0.11)	0.01 (0.11)	-0.12 (0.12)	0.08 (0.13)	0.07 (0.13)	0.29 (0.18)
	10 days shorter	0.4 (0.14) **	0.41 (0.11) ***	0.41 (0.11) ***	0.31 (0.12) **	0.46 (0.13) ***	0.82 (0.13) ***	0.71 (0.19) ***
	15 days shorter	0.38 (0.14) **	0.43 (0.11) ***	0.51 (0.12) ***	0.31 (0.12) **	0.67 (0.13) ***	0.72 (0.13) ***	0.69 (0.2) ***
AI-driven use of your data (Base = No health record data)	Includes health record data	0.04 (0.15)	0.05 (0.11)	-0.03 (0.11)	-0.07 (0.12)	0.01 (0.13)	-0.06 (0.13)	-0.27 (0.2)
AI-driven use of your data (Base = No consent required)	Consent required	0.57 (0.14) ***	0.23 (0.11) *	0.35 (0.11) ***	0.24 (0.12) *	0.24 (0.13) .	0.26 (0.13) *	0.21 (0.19)
AI impact on out-of-pocket costs (Base = No additional costs ($0)	Additional $35	0.3 (0.09) ***	0.18 (0.07) **	0.33 (0.07) ***	0.18 (0.07) *	0.35 (0.08) ***	0.47 (0.08) ***	0.46 (0.11) ***
	Additional $50	0.08 (0.09)	0.13 (0.07) *	0.16 (0.07) *	0.1 (0.08)	0.15 (0.08) .	0.24 (0.08) **	0.21 (0.12) .
	Additional $100	-0.19 (0.08) *	-0.05 (0.07)	-0.21 (0.07) **	-0.05 (0.07)	-0.18 (0.08) *	-0.15 (0.08) *	-0.05 (0.11)
Observations		960	1568	1504	1376	1200	1296	624
LL		-588	-980	-944	-837	-697	-731	-339
AIC		1202	1985	1913	1670	1419	1488	702
BIC		1265	2055	1983	1768	1486	1555	760

AIC: Akaike information criterion; BIC: Bayesian information criterion; LL: log-likelihood; SE: standard error.
Note: *** p=0, ** p=0.001, * p=0.01, . p=0.05

Table 6.11: MNL model: subgroup analyses by education

		Year 11 and below	**Year 12 or equivalent**	**Certificate (any level including trade certificate)**	**Diploma/advanced diploma**	**Bachelors on honours degree**	**Post graduate degree (Masters or Doctorate)**
Attribute	**Level**	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**
Accuracy (Base = same as clinicians)	The AI system sometimes misses cancer	0.9 (0.15) ***	0.87 (0.12) ***	0.74 (0.13) ***	0.81 (0.13) ***	0.84 (0.09) ***	1.06 (0.15) ***
	The AI never misses cancer but	1.35 (0.16) ***	1.11 (0.12) ***	1.2 (0.14) ***	1.26 (0.14) ***	0.99 (0.09) ***	0.98 (0.15) ***

		Year 11 and below	Year 12 or equivalent	Certificate (any level including trade certificate)	Diploma/advanced diploma	Bachelors on honours degree	Post graduate degree (Masters or Doctorate)
Attribute	**Level**	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**	**Estimate (SE)**
	sometimes calls normal tissue cancer						
	The AI system is less likely to miss cancer and less likely to call healthy tissue for cancer	1.44 (0.16) ***	1.29 (0.12) ***	1.46 (0.14) ***	1.24 (0.14) ***	1.37 (0.09) ***	1.18 (0.15) ***
Diagnosis and treatment oversight (Base = Assistive)	Fully autonomous	-0.5 (0.09) ***	-0.17 (0.07) **	-0.21 (0.08) **	-0.37 (0.08) ***	-0.18 (0.05) ***	-0.18 (0.08) *
AI impact on time to cancer treatment (Base =No change (30 days))	10 days longer	-0.19 (0.14)	-0.05 (0.12)	0.1 (0.13)	-0.03 (0.13)	-0.08 (0.08)	0.07 (0.14)
	10 days shorter	0.35 (0.15) *	0.46 (0.12) ***	0.56 (0.12) ***	0.43 (0.13) ***	0.43 (0.08) ***	0.69 (0.14) ***
	15 days shorter	0.35 (0.15) *	0.47 (0.12) ***	0.62 (0.13) ***	0.47 (0.13) ***	0.52 (0.09) ***	0.6 (0.15) ***
AI-driven use of your data (Base = No health record data)	Includes health record data	0.13 (0.15)	-0.04 (0.12)	0.05 (0.13)	-0.21 (0.13)	-0.01 (0.09)	-0.07 (0.15)
AI-driven use of your data (Base = No consent required)	Consent required	0.34 (0.14) *	0.51 (0.12) ***	0.27 (0.13) *	0.1 (0.13)	0.25 (0.08) **	0.31 (0.14) *
AI impact on out-of-pocket costs (Base = No additional costs ($0)	Additional $35	0.37 (0.09) ***	0.25 (0.07) ***	0.38 (0.08) ***	0.28 (0.08) ***	0.28 (0.05) ***	0.35 (0.09) ***
	Additional $50	0.14 (0.1)	0.13 (0.07) .	0.03 (0.08)	0.23 (0.08) **	0.18 (0.05) ***	0.14 (0.09)
	Additional $100	-0.14 (0.09)	-0.08 (0.07)	-0.09 (0.08)	-0.23 (0.08) **	-0.14 (0.05) **	-0.09 (0.09)
Observations							
LL		960	1424	1200	1136	2816	976
AIC		-557	-867	-718	-683	-1711	-590
BIC		1140	1759	1463	1391	3448	1206

AIC: Akaike information criterion; BIC: Bayesian information criterion; LL: log-likelihood; SE: standard error.
Note: *** p=0, ** p=0.001, * p=0.01, . p=0.05

Feedback questions

Responses to question regarding DCE task difficulty suggest that most respondents did not find the DCE tasks overly difficult and were able to differentiate between the options presented (Figure 6.4 and Figure 6.5).

Figure 6.4: DCE follow-up questions (N=533)

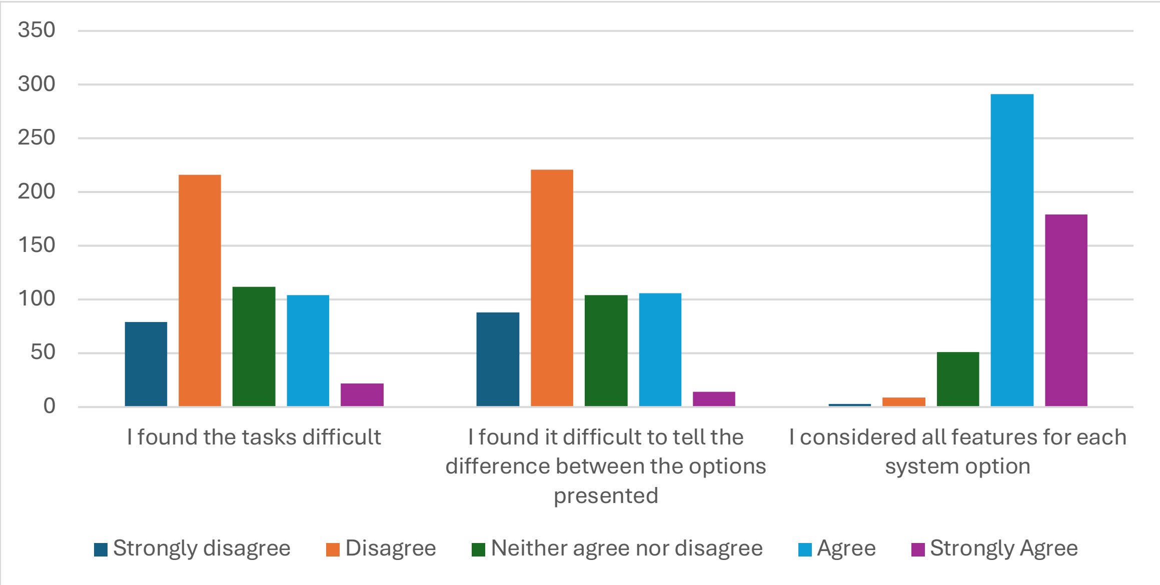
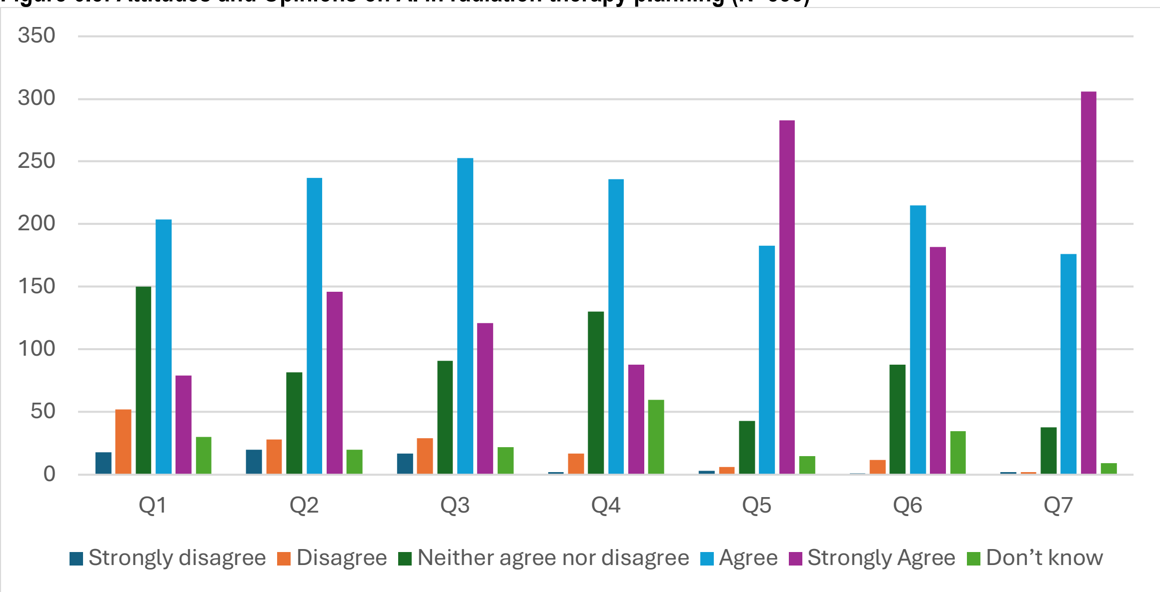


Figure 6.5: Attitudes and Opinions on AI in radiation therapy planning (N=533)



AI: artificial intelligence; DCE: discrete choice experiment; RT: radiation therapy
Notes:
Q1. The benefits of using AI to analyse medical images outweigh the risks
Q2. I would grant permission to use my personal data
Q3. I would be in favour of using AI to interpret medical images as decision support for clinicians
Q4. The implementation of AI may impact my healthcare costs
Q5. AI systems should be tested by an independent authority before they are used on patients
Q6. I would like my physician to override the recommendations of AI
Q7. I would like to be informed about the use of AI in my diagnosis and treatment

Discussion

The findings from this study provide significant insights into the preferences and attitudes of patients regarding the use of AI in the delivery of radiation therapy. This is the first paper to explore the general population's preferences regarding the use of AI in radiation therapy treatment planning and delivery. The results underscore the crucial role that accuracy, cost and timeliness play in the acceptance of AI systems, as well as ethical concerns and autonomy preferences of potential users.

Respondents preferred AI systems that demonstrate higher accuracy in identifying cancerous tissues compared to conventional clinician assessments. This refers to the necessity for AI systems to meet high accuracy standards to gain acceptance. However, it is acknowledged that the levels of the “accuracy” attribute are expressed in language that may oversimplify the nuanced nature of diagnostic performance. The levels of accuracy were formulated in qualitative terms based on the understanding that (according to fuzzy-trace theory); people often extract the qualitative gist of a risk when interpreting it. This involves making qualitative distinctions similar to those presented in our discrete choice experiment (DCE), which rely on relative comparisons rather than literal, quantitative computation (Brust-Renck et al. 2013). Although described as the AI system’s ability to correctly identify cancerous or healthy tissues in medical images, this broad framing may not adequately reflect the trade-offs between false positives and false negatives, which could have potentially introduced ambiguity, leading respondents to rely on their own assumptions. It is acknowledged that the use of this qualitative and relative approach may be at risk of oversimplifying the nuanced nature of diagnostic performance, particularly in relation to false positives and false negatives, in a way that may not unambiguously situate AI performance relative to clinicians across all levels. This needs to be considered when interpreting coefficients and willingness-to-pay (WTP) estimates, and future DCEs could include quantitative anchors for sensitivity, specificity, or missed cancer rates. That approach would allow direct mapping of preferences to the performance characteristics of candidate AI tools but may also lose the nuance of asking respondents to consider their underlying attitudes regarding clinician versus AI interpretation of accuracy. These issues were raised in a Letter to the Editor published in Value in Health in relation to the publication derived from the work presented in this chapter. They were addressed in the corresponding author response and should be borne in mind when interpreting the results (see Figure A6.4, Attachment 6).

Timeliness also emerged as a significant factor, with respondents valuing systems that could expedite cancer treatment, reflecting the pressing need for timely care in oncology settings and highlighting the need for a balanced approach that optimises both accuracy and speed without compromising quality. Higher costs were associated with a lower perceived value of AI. However, the predefined cost range used in this DCE may have been limited to fully capture respondents’ willingness to pay for certain AI-related attributes. Although there was some acceptance of autonomous AI systems, the preference for clinician oversight remains strong. This indicates that while patients may appreciate the efficiencies brought by AI, they also prioritise the human element in patient care, seeking a shared-decision model where clinicians and patients share the best available evidence (Elwyn et al. 2012) rather than a replacement of clinicians with AI technology. The mixed preferences regarding medical data use highlight the complex dynamics surrounding consent and privacy in healthcare settings. While some respondents indicated a willingness to forego explicit consent for the use of their health data in favour of granting access to their data and the potential positive impact on treatment effectiveness and prognosis, others expressed a strong desire to maintain control over their personal information. These findings suggests that healthcare organisations must navigate these preferences, ensuring that ethical standards are upheld while fostering trust in AI technologies. This requires evaluation of AI recommendations by healthcare professionals, recognising AI limitations while maintaining accountability for patient care.

Despite the growing volume of research that provides evidence that AI improves accuracy compared with human based systems, the accuracy of medical AI should not be conflated with efficiency (Jongsma et al. 2024). Previous research showed that while AI systems demonstrate high accuracy in tasks that are challenging for healthcare professionals, this does not automatically translate to a reduction in workload or increased efficiency. The development and integration of AI requires significant human labour and expertise, which can ultimately increase workloads rather than reduce them. Furthermore, the successful implementation of AI depends on healthcare professionals' trust and competence in using these systems. Hence, the AI's benefits should be critically evaluated, and it is essential to distinguish between effectiveness (getting more done) and efficiency (doing it with fewer resources) (Jongsma et al. 2024).

Respondents’ preference for AI systems that are assistive rather than fully autonomous resonates with concerns regarding accountability and the potential for AI to make erroneous decisions without human intervention, raising questions about the ethical implications of AI deployment in healthcare settings. As highlighted in recent literature, these algorithms can perpetuate historical biases embedded in their training data, leading to discriminatory outcomes in high-stakes areas such as criminal justice and education (Busuioc 2021). Algorithmic bias can lead to disparities in diagnosis, treatment and outcomes among different patient groups. It can impact on principles of fairness, justice and equity in health, eroding trust in the healthcare system (Harishbhai Tilala et al. 2024). The complexities of machine learning models pose challenges for transparency, making it difficult for public administrators to effectively oversee their functioning and ensure accountability. Furthermore, the reliance on proprietary algorithms exacerbates these issues, as many details about their operation remain undisclosed, hindering efforts to interrogate and challenge algorithmic decisions. These complexities underscore the necessity for regulatory frameworks that prioritise the use of AI systems that provide insight into their workings to safeguard against the unintended consequences of algorithmic decision-making (Busuioc 2021).

The implications of these findings extend to the development and implementation of AI systems in healthcare. To mitigate issues of bias and underrepresentation in AI training data, which can compromise accuracy, it is essential to expand training datasets to include diverse populations that reflect the demographics of the patient population. This approach will enhance the generalisability and reliability of AI algorithms, ultimately leading to improved patient outcomes and greater acceptance among consumers. Previous research highlights that perceived usefulness, performance expectancy, attitudes, trust, and effort expectancy are critical predictors of behavioural intention to adopt AI technologies across various sectors (Kelly et al. 2023).

In addition, a comprehensive evaluation of an AI system's performance should be conducted through collaboration between developers, clinicians, and healthcare service consumers to confidently establish its ability to perform specific tasks within real-world clinical workflows. This process can be supported by translational trials, which serve as a critical testing stage for AI in healthcare (McCradden 2024; McCradden, Joshi, et al. 2020).

Overall, this DCE offers valuable insights for adopting of AI in radiation therapy highlighting its potential to streamline processes, improve outcomes, and reduce costs (Kalsi et al. 2024). However, this study is limited by the practical constraints of the survey design, testing only two hypothetical AI systems with five attributes, which may not fully capture the complexity and breadth of features that influence real-world decision-making. In practice, AI systems used in healthcare may involve a wider range of attributes, such as interoperability, patient safety, regulatory compliance, cost-effectiveness, and user training requirements, that could potentially affect stakeholder preferences.

The out-of-pocket cost attribute levels were informed by previous Australian study exploring costs in radiotherapy settings (van Gool et al. 2023) , given that the DCE recruited general public rather than patients with cancer. We acknowledge that these values are substantially lower than those reported in research investigating the costs of radiotherapy (Batumalai et al. 2019). Future work should incorporate a broader range of cost levels to better test their impact on willingness-to-pay estimates and ensure that the resulting values are realistic and policy relevant. The out-of-pocket cost attribute levels were informed by previous Australian study exploring costs in radiotherapy settings (van Gool et al. 2023) , given that the DCE recruited general public rather than patients with cancer. We acknowledge that these values are substantially lower than those reported in research investigating the costs of radiotherapy (Batumalai et al. 2019). Future work should incorporate a broader range of cost levels to better test their impact on willingness-to-pay estimates and ensure that the resulting values are realistic and policy relevant.

Another potential limitation of this study relates to the general population sample and their varying levels of understanding and experience with cancer. Given the complexity of cancer care, respondents with limited personal or professional exposure may have found it challenging to interpret the scenarios accurately or fully engage with the hypothetical tasks. Although the survey included questions to gauge self-reported knowledge (59%) and experience (14%) with cancer, self-assessments of understanding may not reliably reflect true comprehension, particularly for a nuanced topic like oncology. Respondents were not specifically primed or provided with detailed background information prior to completing the tasks, which may have further impacted their ability to make informed trade-offs.

In conclusion, this study highlights the importance of optimising AI systems for accuracy and timeliness while addressing ethical concerns surrounding autonomy and data privacy. The findings indicate a need for ongoing discussions and collaborations among stakeholders, including healthcare professionals, patients, and AI developers, to ensure that AI technologies prioritise patient safety and care quality. Future research should explore these dynamics, focusing on the integration of AI into clinical workflows and the implications for patient-provider relationships.

Chapter 7: Evaluation of the Australian National Digital Health using Best-Worst Scaling

Abstract

Background: Australia's National Digital Health Strategy (NDHS) 2023-2028 provides a framework for healthcare transformation through digital innovation. While existing maturity assessment models evaluate organisational capabilities, they rarely incorporate public input. This research addresses this gap by exploring how individuals in general population prioritise digital health initiatives across the Strategy's four outcomes: digitally enabled systems, person-centred care, inclusive access, and data-driven decision-making. Using Best-Worst Scaling (BWS) methodology, this study examines which initiatives matter most to the public, ensuring digital transformation aligns with community values and expectations rather than solely with institutional priorities.

Methods: This study involved conducting a BWS experiment to assess public priorities within the 80 initiatives included in the NDHS. Respondents were asked to select both the most and least important initiatives from sets of five initiatives. They were shown 27 such sets of 5 initiatives. Data were analysed using count analysis, multinomial logit, mixed logit, and latent class models to generate robust preference rankings and identify population segments with distinct priorities.

Results: Analysis of data from 548 representative Australian adults revealed that the most important initiatives to respondents were "Protecting health information against cyber-attacks" and "Ensuring current, accessible information about healthcare providers and services." Conversely, "Preparing for new technologies like AI and genomics" and "Participating in digital health evaluations" ranked lowest in priority. Statistical modelling confirmed significant differences between highest and lowest-ranked initiatives. Mixed logit modelling revealed significant preference heterogeneity for most initiatives, indicating varying priorities across individuals. Latent class analysis identified distinct preference segments within the population. The results were largely consistent across demographic subgroups, with some variation in preferences among IT professionals, suggesting broad consensus on digital health priorities.

Conclusions: The findings underscore the importance of incorporating public input into digital health strategy development. By identifying and prioritising initiatives that resonate most with the public, policymakers can ensure that digital health transformations are not only technologically advanced but also aligned with community values and expectations. This alignment is crucial for fostering public trust and engagement in digital health initiatives. Future research should continue to explore public

preferences and expand the scope to include diverse demographic groups to further refine and enhance digital health strategies.

Introduction

Strategies for implementing digital technologies that support an organisation's digital transformation goals have been widely explored, particularly in light of the recent growth in application of artificial intelligence (AI). These technologies present both significant opportunities and complex challenges for adoption, requiring thoughtful planning and alignment with organisational capabilities and strategic objectives (Holmström 2022).

To maximise the potential of digital technologies such as AI, both organisational transformation and technological adoption are essential. Given the complexity and the evolving nature of these technologies, AI in particular, their successful implementation requires ongoing, multifaceted adaptations informed by user feedback and experience. This includes adapting organisational resources, workforce capabilities, culture, and decision-making processes, all of which are evolving in parallel with technological advancements (Holmström 2022).

However, this can be challenging due to the inherent complexities of healthcare systems, legacy technological infrastructure, and rigid policies that may not be sufficiently flexible to accommodate innovative technologies. These technologies often require substantial investment and specialised human resources, frequently sourced from private consulting, highlighting a persistent gap between their potential and their actual use within organisations (Koutsoukis 2025).

Digital strategies can play an important role in bridging this gap by providing a coherent framework and policy direction that encourages the integration of emerging digital health technologies (DHTs). By aligning organisational goals with broader national objectives, these strategies can help streamline investment, foster public-private partnerships, and promote capacity-building initiatives that support sustainable digital transformation in healthcare.

The National Digital Health Strategy NDHS aims to provide a comprehensive roadmap for transforming healthcare through digital innovation, with ambitious initiatives spanning multiple sectors. At its core is the goal of advancing digital health maturity, a critical foundation for the effective implementation and scaling of DHTs. Achieving this requires modernising Australia's digital health infrastructure to support a more integrated and responsive ecosystem, capable of accommodating innovations such as genomics, AI, and sensor-based technologies (ADHA 2023a). A mature digital ecosystem leverages health technology to enable advanced data analytics, improve clinical decision-making, and strengthen public health policy and research. Through targeted investments in infrastructure, workforce development, interoperability, and governance, the NDHS provides a structured framework for assessing and strengthening digital capabilities. These efforts not only prepare health systems for the technical demands of innovative health technologies, such as the use of AI in oncology, but also cultivate a culture of innovation, ensuring that digital tools are seamlessly embedded into clinical workflows and aligned with patient needs.

National strategies need to be accepted by the individuals, organisations and communities they aim to serve. However, the preferences and opinions of those who are the recipients of these policies and healthcare services may differ from those of the policymakers and decision-makers responsible for designing and implementing them.

Evaluation of national strategies is a crucial aspect of policymaking and public administration, as it helps to inform whether the priorities included in the strategy are accurately represented and aligned with public needs, expectations, and values (Cummings 2024). The evaluation process ensures that policies and programs are in line with the priorities supported by the population while also identifying gaps between government actions and public expectations. The evaluation process involves continuous monitoring, stakeholder engagement, and the use of key performance indicators (KPIs) to measure impact (Biggs et al. 2019).

Engaging the general population in determining how publicly funded healthcare resources should be allocated ensures digital health transformations reflect community needs and values, aligning with their priorities and preferences. While existing digital health maturity assessment models such as the Health Information and Management System Society (HIMSS) Digital Health Indicator (DHI), and regional frameworks provide structured methods for evaluating digital capabilities, they often lack direct input from the general population.

This chapter presents a study designed to elicit preferences of potential recipients of health care services. This research addresses this gap by seeking to understand public perspectives on prioritising digital health initiatives. BWS methodology was chosen as being appropriate understanding public preferences for digital health initiatives and priorities, to inform consideration of the extent to which public investment aligns with population preferences for resource allocation. By exploring how individuals perceive and prioritise the initiatives in the NDHS, the study aims to bridge the traditional top-down approach with bottom-up public input. The results of the BWS survey provide insights for the priority setting of the digital health initiatives that are included in the NDHS, which are important for achieving sustainable, inclusive, and person-centred health outcomes for Australians.

Methods

Survey development

A BWS survey was developed and implemented to identify which initiatives included in the NDHS are perceived as most and least important by the general population, including different groups such as patients and health providers/professionals. The survey design and the items included in the BWS were based on the initiatives described in the NDHS.

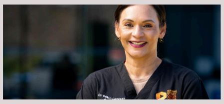
The survey included background information about the NDHS and the research question, which was then followed by seven sections (see Figure A7.2, Appendix 7). The structure of the survey is presented below:

- **Section 1**: Respondent's background and demographic information part 1
- **Section 2**: BWS: 9 initial choice tasks
- **Section 3** Respondent's background and demographic information part 2
- **Section 4:** BWS additional 9 choice tasks
- **Section 5:** Respondent's background part 3
- **Section 6:** BWS final 9 choice tasks
- **Section 7:** Follow-up questions including questions about the difficulty of the survey and questions about respondent's priorities related to digital health initiatives

The survey was structured in a way to limit respondents' fatigue by interspersing the choice tasks with questions about respondent's background and attitudes. The context for the BWS was introduced via a vignette (Figure 7.1) which included a short (30sec) video presenting the NDHS (https://youtu.be/l1O7ox28xYM) and information shown below:

Figure 7.1: BWS survey Vignette

The National Digital Health Strategy (2023-2028) in Australia aims to improve the quality, safety and efficiency of the healthcare system through integration of digital technologies. The strategy seeks to achieve 4 outcomes for Australia's health system as presented below:



Digitally enabled

Creating health and wellbeing services that are connected, safe, secure and sustainable.

Person-centred

Ensuring Australians are empowered to look after their health and wellbeing and equipped with the right information and tools.

Inclusive

Providing Australians with equitable access to health services, when and where they need them.

Data-driven

Ensuring data is readily available and informs decision making about individuals, communities and national issues.

The strategy includes specific initiatives that outline priority actions, guiding partners in their contributions to its implementation. We will ask you to identify the initiatives you consider most and least important. Your feedback will help policymakers improve digital health initiatives to better meet the needs of Australians.

Each respondent was asked to complete 27 BWS choice tasks. In each choice task, respondents were shown a list of five initiatives and were asked to indicate which of the listed initiatives was most important to them and which least important to them. An example choice task is presented in Figure 7.2. The BWS choice tasks were divided into three sections, where 9 choice tasks were presented in each section. Before the actual choice tasks, the respondents were presented with a tutorial to guide them through the components of the choice tasks and instructions on how to complete the tasks (see Figure A7.2, Appendix 7). Additional background questions were presented in between the sets of 9 choice tasks to break up the presentation of the BW tasks to reduce respondent fatigue (Nguyen et al. 2022). The final 9 choice tasks of the survey were followed by questions about the survey and a final question asking respondents to provide feedback about the survey or the topic in general.

Figure 7.2: Example of BWS choice task

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is most important to you and which of these initiatives is least important to you. *Please note there are no right or wrong answers here, we are interested in your opinion.*

Most Important	*Task 1 of 27*	Least Important
○	**Assist care homes in connecting to the online health record system, My Health Record**	○
○	**Make it easier for general practitioners (GPs) to share information and access data**	○
○	**Expand online tools to help people record their medical wishes for aged care**	○
○	**Build a system to share health information safely across the country**	○
○	**Combine services for newborns, so parents can register their baby and access benefits more easier**	○

BWS items

The development of items for the BWS exercise was based on the original 80 initiatives included in the NDHS Delivery Roadmap (ADHA 2023b). Because the initiatives are worded in technical and policy-oriented language, they were reviewed and re-worded to improve comprehensibility for the general population respondents. This process involved reviewing and modifying the wording of the initiatives through consultations with senior researchers (DS, RV) experienced in stated preference (SP) research. Their input helped to ensure the initiatives were clearly worded, contextually relevant, and easily interpretable by respondents. Specific attention was paid to phrasing, terminology and cognitive burden to maximise comprehension and reduce ambiguity during survey completion (Table 7.1). The refinement process involved an initial independent rephrasing by ML, followed by independent reviews from RV and DS, and concluded with an extensive review by all three researchers to reach consensus-based approach.

Table 7.1: BWS items (N=80)

Item no.	Description- Original NDHS	Description- used in BWS
0	Develop and maintain a national secure messaging capability to enable the safe exchange of clinical documents	Create secure national system for safely sharing health-related documents like clinical notes
1	Continue roll out of Provider Connect Australia to ensure availability of up-to-date information about healthcare providers	Make sure information about health care providers and health services is always current and easy to access
2	Assist software vendors to connect residential aged care facilities to My Health Record	Assist residential aged care facilities in connecting to the online health record system, My Health Record
3	Connect multiple government services to newborn enrolment information by rolling out the Birth of a Child project nationally	Roll out a national newborn enrolment system that connects to government services
4	Advance the use of electronic referrals, transfers of care and discharge summaries as business as usual	Make the use of electronic referrals, transfers of care and discharge summaries business as usual
5	Update healthcare provider systems to strengthen and support electronic prescribing	Update healthcare provider systems to strengthen and support electronic prescribing
6	Assist software vendors to connect allied health providers to My Health Record	Help aged care software developers to align with My Health Record and the Aged Care Transfer Summary
7	Finalise clinical information system standards for residential aged care facilities	Standardise clinical information systems for residential aged care facilities
8	Enhance and expand advance care planning documents to support end-of-life decisions, ongoing care and treatment preferences	Improve and update advance care planning documents to support end-of-life decisions and ongoing care preferences
9	Implement the National Digital Health Capability Action Plan	Implement the National Digital Health Capability Action Plan
10	Develop a digital health workforce readiness framework for organisations to self-assess and plan their digital health workforce development	Develop a framework to help organisations ensure their health workforce is digital health ready
11	Pilot and evaluate the national digital health capability framework and self-assessment tool to improve digital	Improve digital health skills of the health and care workforce in residential aged care facilities

Item no.	Description- Original NDHS	Description- used in BWS
	health skills of the health and care workforce in residential aged care facilities	
12	Develop guidelines and resources for digital health learning, education and practice	Develop guidelines and resources for digital health learning, education and practice
13	Develop an online hub to host and connect curated digital health workforce content	Create an online platform to share and connect digital resources for the health workforce
14	Uplift digital health capabilities in primary care to improve interoperability between systems and streamline and simplify data access	Make it easier for primary care providers to share information and access data
15	Develop and operate digital solutions that support the career and learning pathways of healthcare providers and their mobility across the sector	Build digital tools that support healthcare providers in their training and career paths
16	Continue modernising digital health infrastructure including My Health Record with contemporary architectures to make information more accessible and discoverable	Modernise platforms like My Health Record to make them faster and easier to use
17	Mandate electronic prescribing for medicines that are high cost and/or high risk through updates to technology, standards and regulation	Create accurate terms and standardised rules to ensure systems work well across healthcare settings
18	Develop Fast Health Interoperability (FHIR®) core standards that set the minimum requirements to support consistent capture and sharing of health information	Set standards for sharing health data with consistent rules to make it easier to share health information across systems
19	Continue to implement standards and resilience measures to protect personal health information and digital health infrastructure from cyber-attack, natural disasters and climate event	Protect Health Information and infrastructure against cyber-attacks and natural disasters
20	Co-design technical, clinical terminology and exchange standards for a national electronic requesting capability for diagnostic imaging and pathology	Develop a national system for online requests for blood tests and X-rays
21	Embed interoperability in procurement in accordance with national interoperability procurement guidelines	Require new healthcare technology to work well with existing systems
22	Mandate electronic prescribing for medicines that are high cost and/or high risk through updates to technology, standards and regulation	Require electronic prescribing for expensive or high-risk medicines by updating technology and rules
23	Increase digital maturity to enable efficient data collection, analysis and use of national clinical quality registries in line with the Framework for Australian Clinical Quality Registries	Improve digital systems to collect, analyse, and use data from national health registries more effectively
24	Co-design, deliver, promote and participate in consumer digital health literacy programs and integrate with broader government digital literacy programs	Involve consumers in the design and delivery of digital health literacy programs
25	Use guidelines, such as the Assessment Framework for mHealth Apps, when developing consumer facing digital health products that meet a range of consumer needs and levels of digital health literacy	Work with consumers to design health tools that are easy to use and accessible
26	Undertake research and evaluate effectiveness of digital health literacy programs to inform program development	Undertake research on the effectiveness of digital health literacy programs
27	Consider digital health literacy in national safety and quality standards	Make digital health literacy part of national safety and quality standards
28	Develop a National Health Information Exchange Architecture and Roadmap that will establish the national technical infrastructure requirements and direction to	Build a system to allow real time sharing of health information safely across care settings nationally

Item no.	Description- Original NDHS	Description- used in BWS
	enable consistent, secure, safe and discoverable near real-time sharing of health information across care settings, with consent, regardless of where the data is stored	
29	Enable consumers, carers and healthcare providers to access key aged care information such as the aged care assessment summary in My Health Record	Enable consumers, carers and healthcare providers to access key aged care information in My Health Record
30	Enable key health information to be made easily available to support transfer of care between residential aged care and acute care settings	Enable key health information to be easily shared to support transfer of care between residential aged care and hospitals
31	Support Real Time Prescription Monitoring (RTPM) to provide clinical decision-making support for prescribers and dispensers	Support clinicians and pharmacists to track and manage medicines and prescriptions in real time
32	Deliver a Prescription Delivery Service that supports the ongoing uptake of electronic prescribing, the expanded use of electronic medication charts and the use of electronic prescribing for high-risk and high-cost medicines	Develop and deliver systems to support electronic prescribing and electronic medicines charts for high risk and high costs medicines
33	Support the use and expansion of electronic prescribing, including the delivery of operational support such as incident management for the Prescription Delivery Service	Develop and expand operational support for electronic prescribing including incident management support
34	Establish regulatory requirements and changes to national accreditation standards to require private and public healthcare providers to share information to My Health Record by default, starting with diagnostic imaging and pathology. This will include providing technical and registration support, education and training	Establish regulations for private and public healthcare providers to share information with My Health Record by default
35	Expand functionality and health information available in my health app to better support consumers, such as structured pathology, electronic prescriptions, aged care transfer summaries and Medicare information	Add new features to My Health App to better support consumers e.g., electronic prescriptions and test results
36	Engage consumers in co-design and improvements to digital health solutions such as my health app and My Health Record	Involve consumers in improving tools like My Health Record and My Health App
37	Develop a roadmap to support the allied health sector and software vendors to upload clinical content to My Health Record	Assist physiotherapists, dietitians, and other allied health providers in sharing their records on My Health Record
38	Implement widespread adoption and use of national healthcare identifiers for individuals, healthcare providers and healthcare provider organisations	Implement unique national healthcare identifiers for individuals and healthcare providers
39	Connect hospital clinical information systems to the National Health Information exchange	Connect hospital clinical information systems to the National Health Information exchange
40	Enable pregnancy and child health information to be shared and accessed through national digital health infrastructure	Allow pregnancy and child health information to be shared and accessed through national digital systems
41	Uplift the Pharmacist Shared Medicines List to enable structured medicines information to be discoverable and available in the My Health Record System	Improve systems to allow medicines information to be accessed and shared through My Health Record
42	Share information by default to support multidisciplinary care, including aged care plans and GP management plans	Automatically share information to support multidisciplinary care, including aged care and GP management plans
43	Support secure information sharing by enhancing authentication services	Support secure information sharing by enhancing authentication services

Item no.	Description- Original NDHS	Description- used in BWS
44	Identify options to develop a national health legislative framework authorising health information sharing across care settings and borders	Develop legislation to allow health information sharing across care setting and borders
45	Implement system changes to store and manage individual and organisational healthcare provider details	Implement systems to store and manage healthcare provider details
46	Progress integration between the national digital identity solution and healthcare systems	Progress integration between the national digital identity solution and healthcare systems
47	Review and implement regulatory requirements for consent management for access and use of patient health information	Improve regulatory requirements to manage consent for access and use of patient health information
48	Ensure service provider details in healthcare provider directories are accurate and kept up to date	Ensure provider details in health care provider directories are accurate and kept up to date
49	Provide digital solutions to support expanded delivery of home-based care, such as hospital delivered in the home and services provided in residential care facilities	Provide digital tools to support expanded delivery of home-based care
50	Evaluate virtual care models, policy tools and mechanisms that support team-based, multidisciplinary primary and specialist care and identify opportunities for further investment	Evaluate virtual care and policy tools that support team based multidisciplinary care.
51	Identify, design and build digital capabilities required to improve and scale virtual care, particularly in rural and remote areas	Build tools to improve and expand virtual care, particularly for remote and rural communities
52	Develop and design capabilities that support the sharing of health information from personal devices	Develop and design ways to support the sharing of health information from personal devices
53	Develop capabilities to enable healthcare provider systems to collect and display health information from personal devices	Create systems that let healthcare providers to collect and display health information from personal devices securely
54	Incorporate standards and develop infrastructure to support the sharing of health information from personal devices with healthcare providers	Develop guidelines to support the sharing of health information from personal devices with healthcare providers
55	Establish governance and a framework to support adoption, use of personal devices and sharing of personal health information	Create rules and plans to safely use personal devices for sharing health information
56	Support the design, development, and enhancement of digital infrastructure to enable integrated mental healthcare screening, assessment, navigation, referral and treatment	Create better systems to help people access mental health services
57	Identify options to improve data integration between the health and disability systems	Make it easier to share information between the health and disability systems
58	Enhance digital systems and services that support team-based care for consumers registered with MyMedicare	Improve digital tools to support team-based care for people registered with MyMedicare
59	Support the development of new digital health standards with a focus on priority use cases and emerging technologies	Support development of new digital health standards for emerging technologies
60	Align digital health plans and activities with actions in national, state, territory, and Coalition of Peaks Closing the Gap Implementation Plans	Align digital health plans and activities across national, state, territory Closing the Gap Implementation Plans
61	Engage consumers who experience barriers to healthcare access, and peak health and community organisations to uptake, access, use and co-design digital health solutions	Involve consumers who face barriers in using healthcare, and health and community groups, in design of digital health tools

Item no.	Description- Original NDHS	Description- used in BWS
62	Undertake and share research into digital health models of care to inform public health decisions and the translation of the models into clinical practice	Research and share information about digital health care to help translate new models into clinical practice
63	Collect and share patient reported experience and outcomes data to inform decision making, shared care planning and care improvements	Collect and share patient reported experience and outcomes data to improve healthcare
64	Deliver a data analytics capability and implement analytics programs to leverage identified data including for research and public health use once necessary governance and legislative arrangements are established	Develop analysis and governance systems to allow health data to be safely used for health research
65	Australia to participate in discussions to harmonise global aligned standard on health technology exports and reduce costs associated with customising imported global products	Australia to take part in discussion to harmonise global health technology standards and products and to reduce costs
66	Australia is to continue international cooperation to advance secure and interoperable digital health as a core focus of the Global Digital Health Partnership and organisations including WHO, OECD, APEC and G20 Target: ongoing to 2028	Australia to cooperate internationally to improve secure digital health systems
67	Develop mechanisms to ensure Aboriginal and Torres Strait Islander communities have access to data held by government and other relevant entities to support local planning and decision making	Ensure Aboriginal and Torres Strait Islander communities can access data held by government and other relevant entities to support local decision making
68	Support the use of exploratory and simulation research activities to evaluate digital health solutions	Support the use of exploratory and simulation research activities to evaluate digital health solutions
69	Harmonise relevant policy and legislation across jurisdictions to support the safe and secure use of and access to health information	Harmonise relevant policy and legislation across jurisdictions to support the secure use of and access to health information
70	Develop plans for emerging and highly dimensional data such as AI, image analysis and genomics	Get ready for new technologies like AI and genomics in healthcare
71	Uplift national and jurisdictional digital health infrastructure to flexibly accommodate AI, machine learning, deep learning technologies and genomics	Improve national and local digital health systems to allow for use of AI, machine learning, and genomics
72	Monitor and identify emerging data sources and technology that support healthcare	Monitor and identify emerging data sources and technology that support healthcare
73	Identify healthcare related opportunities and risks arising from broader, whole-of economy approaches to the regulation of AI	Identify healthcare opportunities and risks arising from whole-of economy approaches to regulating AI
74	Support adoption of and regulate new medical technology including bioinformatics, AI and mixed reality in settings such as radiology, ophthalmology and triaging	Support and regulate use of new medical technology including bioinformatics, AI and mixed reality in healthcare settings
75	Support implementation of data sharing frameworks for data such as genomics and for My Health Record	Help set up systems for sharing data like genomics and for My Health Record
76	Measure, monitor and report on changes in digital health maturity, adoption, meaningful use and benefits to inform national and local planning	Measure, monitor and report on changes in digital health to help plan for the future
77	Participate in evaluations and provide feedback on experiences of digital health	Participate in evaluations and provide feedback on experiences of digital health
78	Support increased digital health maturity, adoption and meaningful use through increased awareness of digital health benefits among consumers and healthcare providers	Help consumers and healthcare providers to understand and use digital health to improve care
79	Increase access to and integration of clinical quality registries in the broader digital health ecosystem to	Make clinical quality registries more accessible and able to support patient-cantered care

Item no.	Description- Original NDHS	Description- used in BWS
	support patient-centred care and clinical practice improvement	

Initially a draft of the survey was completed by members of the discrete choice experiment group at the Centre for Health Economics Research and Evaluation, University of Technology Sydney (CHERE, UTS), specifically to provide feedback on the number of initiatives presented in each choice task and the overall number of choice tasks to be presented to each respondent. This group also provided suggestions regarding survey comprehension and sequencing.

Designed experiment

The initial design was a balanced incomplete block design (BIBD) based on 81 items and with 324 blocks of size 5. The four base blocks used to obtain this BIBD are given in Julian, Abel and Buratti (2010). Three versions were obtained from each of the 4 base blocks giving 12 versions in total. As there are only 80 initiatives, one of the 81 items was mapped to one of the others so that each version had at least one copy of each initiative. The BIBD and the final choice tasks were generated in Mathematica (Wolfram Research, Inc 2025).

Maximum difference representation of data was used for the analysis, which assumes that each respondent is choosing, from each quintuple presented to them, a pair of items with one being the best available in the quintuple and the other being the worst. There are 20 possible (best, worst) pairs and so each choice task corresponds to 20 rows in the design matrix of which only 1 is chosen.

Data collection

The survey was administered by Pure Profile, an online survey provider with approximately 1 million panel members in Oceania (PureProfile 2022). Panel members who were 18 years and older, living in Australia and able to speak and read English, were invited to participate via an email link which granted access to the survey. Respondents were recruited to be representative of the general population in Australia by age and gender. Panel members were asked to indicate consent at the end of the introduction which contained information about the content and purpose of the study, and they could exit the survey at any point.

Data were collected between 20 December 2025 to 24 January 2025: noting that the first pilot of 50 respondents was collected 20 December to 2 January; an additional pilot of 50 respondents between 13-14 January and the final collection of data from 448 respondents between 19 and 24 January 2025. During the survey pilot phase, the first 100 responses were checked for survey flow and logic before collection of the full sample commenced.

Ethics approval

Ethics approval was granted by the University of Technology Sydney (UTS), Human Research Ethics Committee (HREC) under the CHERE Program Ethics Approval (UTS HREC REF NO. ETH24-9283; Figure A7.1 Appendix 7). Respondents' confidentiality was ensured by ensuring that no identifying information was provided in the data for analysis. All respondents have provided informed consent. Respondents could withdraw from the study at any time and without giving reasons and to request the deletion of the collected data at any time during the survey. Respondents were informed that they could contact the Research Office directly if they had any concerns, they wished to raise independently of the research team. Both a phone number and an email address were provided for this purpose. Researchers' contact information was provided on the first and last page in case the respondents had questions. The respondents could contact the researchers directly by phone or via the contact email address. The respondents were told that the results of this study could be presented at national and international conferences and published in peer-reviewed journals.

Data analysis

Only fully completed surveys were included in the analysis. Data were analysed using four selected analysis methods: count analysis, multinomial logit, mixed logit and latent class analysis. Responses to the demographic information and feedback questions were analysed as descriptive statistics using R Studio.

Count analysis

Responses to the BWS surveys were first summarised using a simple count analysis for each item. Frequency counts for the number of times each of the items are chosen as the best (most important) or worst (least important) is the simplest way to analyse best-worst data. The number of times that each item was chosen as worst was subtracted from the number of times it was chosen as best and divided by the number of times an item appeared (Louviere et al. 2015). This is termed the standardised best-worst score for each item. These scores were used to rank the NDHS initiatives. The standardised best-worst scores can range from -1 (always the worst) to 1 (always the best). A positive score corresponded to items that were chosen as best more often than they were chosen as worst. A negative score corresponded to items that were chosen as worst more often than they were chosen as best. A zero-score indicated that an item was chosen as best and worst an equal number of times or one that was never chosen. Calculations were undertaken using Mathematica (Wolfram Research Inc. 2025) and RStudio (RStudio Team 2024).

Multinomial logit model

Following the initial count analysis, the BWS data were analysed by fitting a multinomial logit (MNL) model to estimate the probability of selecting an item within the NDHS, based on perceived importance relative to the other simultaneously presented options and assuming all respondents have the same underlying preference structure.

The MNL incorporates the logit procedure (where each item has dual coding, best=1 if item is chosen as most important, and best =0 if otherwise; and worst=1 if the item is chosen as least important and worst=0 if otherwise). Hence, as mentioned above, each choice task gives rise to 20 possible vectors and the choice vector indicates which of the 20 (best, worst) vectors was chosen from each choice task presented to each respondent. Data analysis was conducted using mlogit package in R Studio (Croissant 2020). Each item was represented by a coefficient in a vector, β representing the relative preference (importance) of that item, compared to the reference (base) item. The relative preference (importance) of each item indicated the strength and direction of preference for a particular item relative to the base item (Cheung et al. 2019).

The initial MNL model included all items, with the item that was ranked as the most important in the count analysis specified as a base item. Comparison of the coefficients associated with each item made it possible to determine which initiative is most important to respondents. In addition, a robustness check was conducted, where the base item was systematically replaced one at a time in descending order, considering the top five best-performing items and the top five worst-performing items. The results were further analysed within various subgroups of respondents (such as healthcare and IT professionals; subgroups based on age, on gender and on education level).

Mixed logit model

The MNL assumption that all individuals have the same preferences limits the realism of the model. The mixed logit model relaxes the behavioural restrictions on the classic MNL model (i.e. accounts for preference heterogeneity). The model captures heterogeneity by estimating the mean and standard deviation of the parameters. Similar to the multinomial model, the item's coefficient β represents the relative preference (importance) for that item compared with the base item, and their corresponding standard deviation (η), capturing individual-specific unexplained variation around the mean (Cheung et al. 2019). However, this requires simulation methods to estimate. The time needed to run the model increases linearly with the number of draws selected in the model (Molloy 2021), and the size of the datasets. The complexity of this BWS required substantial computational resources, presenting challenges in data processing and analysis. To overcome these issues the logitr package in RStudio was used to conduct the mixed logit analyses. The package is computationally efficient and faster than other similar packages such as mlogit, gmnl and mixl packages in R Studio (Helveston 2023).

The initial model included all items, with the item that was ranked as the most important in the count analysis, specified as a base item. The items included in the model were specified as random parameters and were drawn from a normal distribution using 100 Sobol draws followed by a model using 150 and one using 170 Sobol draws. Sobol sequences are quasi-random low-discrepancy sequences used in simulated maximum likelihood estimation for mixed logit models (Hensher et al. 2018). When increasing the number of draws, the numerical precision obtained for integration increases. However, this also increases RAM and CPU processing time, and a model with 170 Sobol draws was the most that could be run, as higher draw numbers exceeded the computational resources available. Additional models were specified based on a subset of 45 selected items, including 15 best, 15 worst and 15 median items based on the results from MNL model and MaxDiff estimation.

Latent class analysis

The latent class analysis was conducted to identify potential latent segments and hidden heterogeneity among the respondents. This provided additional information on whether the preference for (importance of) an item differs among the respondents. The latent class analysis was explored using different software packages: mlogit function (Croissant 2020) in RStudio and Latent Gold software version 6.1 (Statistical Innovations, Inc 2025) to estimate the optimal number of latent class models, starting with two classes and increasing to six classes. The respondents were classified into clusters with latent class probabilities for each cluster. To determine the number of optimal classes, Aikaike's information criterion (AIC), Bayesian information criterion (BIC) and log-likelihood were used, as these are the preferred indicators for the model choice, where the best fit has the lowest BIC (Cheung et al. 2019).

Results

Sample characteristics

The demographic characteristics of the sample recruited for the survey are presented in Table 7.2. A total of 548 respondents completed the survey and were included in the analysis. The mean time to complete the survey was 28 minutes (SD 83 minutes) and median was 15 minutes (range 2.6 minutes to 24 hours). The age of the respondents was distributed relatively evenly across the age groups and gender, with the highest proportion in age group 35-44 years and with 52% females. The majority of the respondents were born in Australia and lived in metropolitan NSW. Overall, 59% of the respondents had higher education (i.e. diploma/advanced diploma, bachelor's degree and postgraduate degree). Approximately 19% of the respondents worked in healthcare or IT, which is reflective of the Australian general population.

Table 7.2: Respondents demographics characteristics (N=548)

	Respondents, n (%) (N=548)	Australian population (%)
Age[a]		
18-24	57 (10.4)	6.5
25-34	99 (18)	14.7
35-44	96 (18)	14.0
45-54	91 (17)	12.4
55-64	83 (15)	11.4
65-74	88 (16)	9.3
75+	34 (6)	7.8
Gender[a]		
Female	282 (51)	50.9
Male	265 (48)	49.1
Prefer not to say	1 (0.18)	
Born in Australia[a]		
Yes	432 (79)	70.9
No	116 (21)	29.1
State[b]		
ACT	13 (2)	2
NSW	174 (32)	31
NT	5 (1)	1
QLD	110 (20)	21
SA	39 (7)	7
TAS	10 (2)	2
VIC	141 (26)	26
WA	56 (10)	11
Region		
Metro	390 (71)	NR
Regional	158 (29)	NR
City[c]		
Adelaide	33 (6)	5
Brisbane	50 (9)	10
Canberra	13 (2)	2
Darwin	4 (1)	1
Hobart	6 (1)	1
Melbourne	110 (20)	20
Perth	50 (9)	9
Sydney	124 (23)	20
Regional NSW	50 (9)	NR

	Respondents, n (%) (N=548)	Australian population (%)
Regional NT	1 (<1)	NR
Regional QLD	60 (11)	NR
Regional SA	6 (1)	NR
Regional TAS	4 (1)	NR
Regional VIC	31 (6)	NR
Regional WA	6 (1)	NR
Aboriginal origin, Torres Strait Islander origin[d]		
Aboriginal	6 (1)	2.9
Both Aboriginal and Torres Strait Islander	2 (<1)	0.1
Neither	536 (98)	NA
Prefer not to say	2 (<1)	NA
TSI	2 (<1)	0.1
Education[e]		
Post graduate degree (Masters or Doctorate)	69 (13)	12.1
Bachelors or honours degree	171 (31)	20.0
Diploma/advanced diploma	80 (15)	10.3
Certificate (any level including trade certificate)	89 (16)	16.8
Year 12 or equivalent	93 (17)	17.5
Year 11 and below	45 (8)	21.4
Prefer not to say	1 (<1)	NA
Employment[f]		
Carer	3 (1)	69.1
Employed full-time	277 (51)	30.9
Employed part-time	95 (17)	NR
Home duties	24 (4)	NR
Not employed but looking for a job	19 (3)	NR
Not-working student	4 (1)	NR
Other (please specify)	14 (3)	15.7[i]
Retired	111 (20)	69.1
Prefer not to say	1 (<1)	NA
Sectors[g]		
IT	52 (9)	1.3
Education	64 (12)	8.9
Finance	37 (7)	3.8
Government	49 (9)	6.6
Healthcare	52 (9)	15.5
Manufacturing	32 (6)	6.1
Retail	71 (13)	9.3
Other	164 (30)	48.6
Prefer not to say	27 (5)	NA
Professional role (healthcare workers)		
Enrolled Nurse	1 (2)	NA

	Respondents, n (%) (N=548)	Australian population (%)
Registered Nurse	11 (21)	NA
Nurse Practitioner	3 (6)	NA
General Practitioner	1 (2)	NA
Physician	1 (2)	NA
Allied health	9 (17)	NA
Management and administration	13 (25)	NA
Other (please specify)	10 (19)	NA
Prefer not to say	3 (6)	NA
Areas of responsibility (IT professionals)		
IT Infrastructure	11 (2)	NA
Other	2 (<1)	NA
None	3 (1)	NA
Cybersecurity	6 (1)	NA
Software updates	9 (2)	NA
Network infrastructure	2 (<1)	NA
System administration	2 (<1)	NA
Data Management	7 (1)	NA
Cloud computing	8 (1)	NA
Software development	22 (4)	NA
IT Strategy and planning	9 (2)	NA

ABS = Australian Bureau of Statistics; NR: not reported

Notes:

a. ABS, https://www.abs.gov.au/statistics/people/population/births-australia/2022#national, accessed 11 Nov 2024
b. ABS, National, state and territory population September 2024, https://www.abs.gov.au/statistics/people/population/national-state-and-territory-population/sep-2024
c. ABS, Regional population 2023-24 financial year, https://www.abs.gov.au/statistics/people/population/regional-population/2023-24
d. ABS,https://www.abs.gov.au/statistics/people/aboriginal-and-torres-strait-islander-peoples/aboriginal-and-torres-strait-islander-people-census/latest-release
e. ABS, https://www.abs.gov.au/statistics/people/education/education-and-work-australia/latest-release#data-downloads
f. ABS, https://www.abs.gov.au/statistics/labour/employment-and-unemployment/labour-force-australia/oct-2024#employment
g. ABS, https://www.abs.gov.au/statistics/labour/employment-and-unemployment/labour-force-australia-detailed/latest-release#data-downloads, accessed 14 March 2025

The results of questions about respondent's use of healthcare services are presented in Table 7.3. The results show varied healthcare utilisation patterns among respondents. Approximately one-quarter (26%, n=142) reported visiting an emergency department in the past year, while a smaller proportion (20%, n=108) had been hospitalised during that same period. Regarding chronic conditions, 22% (n=121) of respondents reported having been diagnosed with at least one chronic condition. General practitioner visits showed notable variation in frequency: 37% (n=200) visited their GP a few times annually, representing the most common pattern, while 22% (n=120) reported never visiting a GP. More frequent GP utilisation was also observed, with 11% (n=59) visiting monthly, 10% (n=53) weekly, and 6% (n=33) reporting daily visits. These findings indicate diverse healthcare utilisation behaviours across the respondent population, with substantial proportions having recent acute care experiences or ongoing chronic condition management requirements.

Table 7.3: Healthcare utilisation (N=548)

	Respondents, n (%) (N=548)
Have been to ED in the last 12 months	
Yes	142 (26)
No	351 (64)
Prefer not to say	3 (1)
Have been to hospital in the last 12 months	
Yes	108 (20)
No	267 (49)
Prefer not to say	1 (0)
Have been diagnosed with a chronic condition	
Yes	121 (22)
No	248 (45)
Prefer not to say	7 (1)
How often do you visit GP	
Every day	33 (6)
Once a week	53 (10)
Once a month	59 (11)
Few times a year	200 (37)
Never	120 (22)
Prefer not to say	9 (2)

BWS results

The BWS matrix was constructed based on sets of 5 items out of 80 items, choosing the most important ('best') and least important ('worst') in each task. Each respondent completed 27 tasks. Each task generated 20 rows that represent all possible (best-worst) pairs of the 5 items. The outcome column has a 1 in the position corresponding to the row that has the (best, worst) pair chosen. The data matrix has 295,920 rows, being 27x20 rows for each of the 548 respondents.

Count analysis

Table 7.4 presents BWS results using both count analysis and the MNL model. Overall, the respondents identified item 19 ("Protect Health Information and infrastructure against cyber-attacks and natural disasters") and item 1 ("Make sure information about health care providers and health services is always current and easy to access") as the most important, while items 70 ("Get ready for new technologies like AI and genomics in healthcare") and 77 ("Participate in evaluations and provide feedback on experiences of digital health") were least important (Table A7.1, Appendix 7). Between these extremes, a range of items clustered in the middle, indicating moderate importance or divided opinions on their priority. This pattern may highlight areas where respondents see some value but do not feel strongly either way, or where understanding of benefits and impacts varies.

Multinomial logit model

A MNL model was fitted to assess the confidence around the estimates (Table 7.4). The analysis compares preferences for different digital health initiatives, with item 19 ("Protect Health Information and infrastructure against cyber-attacks and natural disasters") used as the reference (base) category in the MNL model. Each row corresponds to a specific item, described in the second column, and categorised by theme presented in the NDHS (e.g. "Data-driven", "Person-centred"). Negative values in both the count and MNL analyses indicate that these items (i.e. item 70, 77 and 26) were selected more frequently as 'worst' than as 'best' compared to the reference item (Table 7.4). The MNL estimates are presented as mean coefficients with standard errors in parentheses. All listed items show statistically significant differences between an estimated preference weight for each item relative to the base item at $p < 0.001$.

The estimated coefficients from the MNL model were consistent with those obtained from count analysis (Table 7.4 and Table A7.1). On average, the respondents assigned the highest relative importance to the item 1 ("Make sure information about health care providers and health services is always current and easy to access"), followed by item 0 ("Create secure national system for safely sharing health-related documents like clinical notes").

The results of the MNL analysis showed that all items were statistically significantly different from the chosen base level (i.e. item 19). The relative importance of item 1 (next best) compared to item 19 was -0.24 (0.07), p<0.01. The relative importance of item 70 (worst/least important) was -1.45 (0.08), p<0.01. Therefore, item 1 yields approximately 6 times as much importance as item 70 (1.45/0.24). The results of the Multinomial Logit (MNL) model robustness check showed that the estimates remained consistent across different base items used in the analysis. Given that the differences in preference weights were not large in magnitude, a refined MNL model was estimated using a reduced set of items. This model included 15 items ranked as best, 15 items ranked as worst and 15 items ranked as medium from the original MNL model with all items and with item 19 used as a base item (Table A7.2, Appendix 7). Sensitivity analyses excluding respondents with very short completion times (quick respondents; Table A7.4 Appendix 7) did not materially alter the estimated preferences, indicating that the results were robust to the exclusion of potentially low-engagement responses, despite substantial variation in survey completion time (mean 28 minutes; median 15 minutes).

Table 7.4: BWS results: count analysis, MNL model (base case item 19) (N=548)

Item	Item description	Theme	Count analysis	MNL Mean (SE)
70	Get ready for new technologies like AI and genomics in healthcare	Data-driven	-0.25	-1.45 (0.08) ***
77	Participate in evaluations and provide feedback on experiences of digital health	Data-driven	-0.24	-1.41 (0.08) ***
26	Undertake research on the effectiveness of digital health literacy programs	Person-centred	-0.19	-1.28 (0.08) ***
3	Roll out a national newborn enrolment system that connects to government services	Digitally enabled	-0.18	-1.27 (0.08) ***
71	Improve national and local digital health systems to allow for use of AI, machine learning, and genomics	Data-driven	-0.16	-1.2 (0.08) ***
66	Australia to cooperate internationally to improve secure digital health systems	Data-driven	-0.16	-1.2 (0.08) ***
50	Evaluate virtual care and policy tools that support team based multidisciplinary care.	Inclusive	-0.14	-1.17 (0.08) ***
24	Involve consumers in the design and delivery of digital health literacy programs	Person-centred	-0.14	-1.17 (0.08) ***
73	Identify healthcare opportunities and risks arising from whole-of economy approaches to regulating AI	Data-driven	-0.14	-1.16 (0.08) ***
67	Ensure Aboriginal and Torres Strait Islander communities can access data held by government and other relevant entities to support local decision making	Data-driven	-0.14	-1.16 (0.08) ***
68	Support the use of exploratory and simulation research activities to evaluate digital health solutions	Data-driven	-0.13	-1.14 (0.08) ***
40	Allow pregnancy and child health information to be shared and accessed through national digital systems	Person-centred	-0.13	-1.13 (0.08) ***

Item	Item description	Theme	Count analysis	MNL Mean (SE)
65	Australia to take part in discussion to harmonise global health technology standards and products and to reduce costs	Data-driven	-0.12	-1.12 (0.08) ***
36	Involve consumers in improving tools like My Health Record and My Health App	Person-centred	-0.11	-1.09 (0.08) ***
75	Help set up systems for sharing data like genomics and for My Health Record	Data-driven	-0.11	-1.06 (0.07) ***
74	Support and regulate use of new medical technology including bioinformatics, AI and mixed reality in healthcare settings	Data-driven	-0.08	-1.02 (0.08) ***
12	Develop guidelines and resources for digital health learning, education and practice	Digitally enabled	-0.08	-1.01 (0.08) ***
15	Build digital tools that support healthcare providers in their training and career paths	Digitally enabled	-0.08	-1.01 (0.08) ***
10	Develop a framework to help organisations ensure their health workforce is digital health ready	Digitally enabled	-0.07	-0.99 (0.08) ***
45	Implement systems to store and manage healthcare provider details	Person-centred	-0.07	-0.98 (0.08) ***
60	Align digital health plans and activities across national, state, territory Closing the Gap Implementation Plans	Inclusive	-0.06	-0.95 (0.08) ***
72	Monitor and identify emerging data sources and technology that support healthcare	Data-driven	-0.06	-0.95 (0.08) ***
49	Provide digital tools to support expanded delivery of home-based care	Inclusive	-0.06	-0.95 (0.08) ***
52	Develop and design ways to support the sharing of health information from personal devices	Inclusive	-0.05	-0.94 (0.08) ***
9	Implement the National Digital Health Capability Action Plan	Digitally enabled	-0.05	-0.94 (0.08) ***
46	Progress integration between the national digital identity solution and healthcare systems	Person-centred	-0.05	-0.93 (0.08) ***
22	Require electronic prescribing for expensive or high-risk medicines by updating technology and rules	Digitally enabled	-0.05	-0.92 (0.08) ***
62	Research and share information about digital health care to help translate new models into clinical practice	Data-driven	-0.05	-0.91 (0.08) ***
38	Implement unique national healthcare identifiers for individuals and healthcare providers	Person-centred	-0.04	-0.91 (0.08) ***
76	Measure, monitor and report on changes in digital health to help plan for the future	Data-driven	-0.04	-0.91 (0.08) ***
55	Create rules and plans to safely use personal devices for sharing health information	Inclusive	-0.03	-0.89 (0.08) ***
7	Standardise clinical information systems for residential aged care facilities	Digitally enabled	-0.03	-0.89 (0.08) ***
25	Work with consumers to design health tools that are easy to use and accessible	Person-centred	-0.03	-0.88 (0.08) ***
13	Create an online platform to share and connect digital resources for the health workforce	Digitally enabled	-0.02	-0.86 (0.08) ***
63	Collect and share patient reported experience and outcomes data to improve healthcare	Data-driven	-0.02	-0.86 (0.08) ***
33	Develop and expand operational support for electronic prescribing including incident management support	Person-centred	-0.01	-0.83 (0.08) ***
58	Improve digital tools to support team-based care for people registered with MyMedicare	Inclusive	-0.01	-0.83 (0.08) ***
6	Help aged care software developers to align with My Health Record and the Aged Care Transfer Summary	Digitally enabled	0	-0.82 (0.07) ***
53	Create systems that let healthcare providers to collect and display health information from personal devices securely	Inclusive	0	-0.81 (0.08) ***

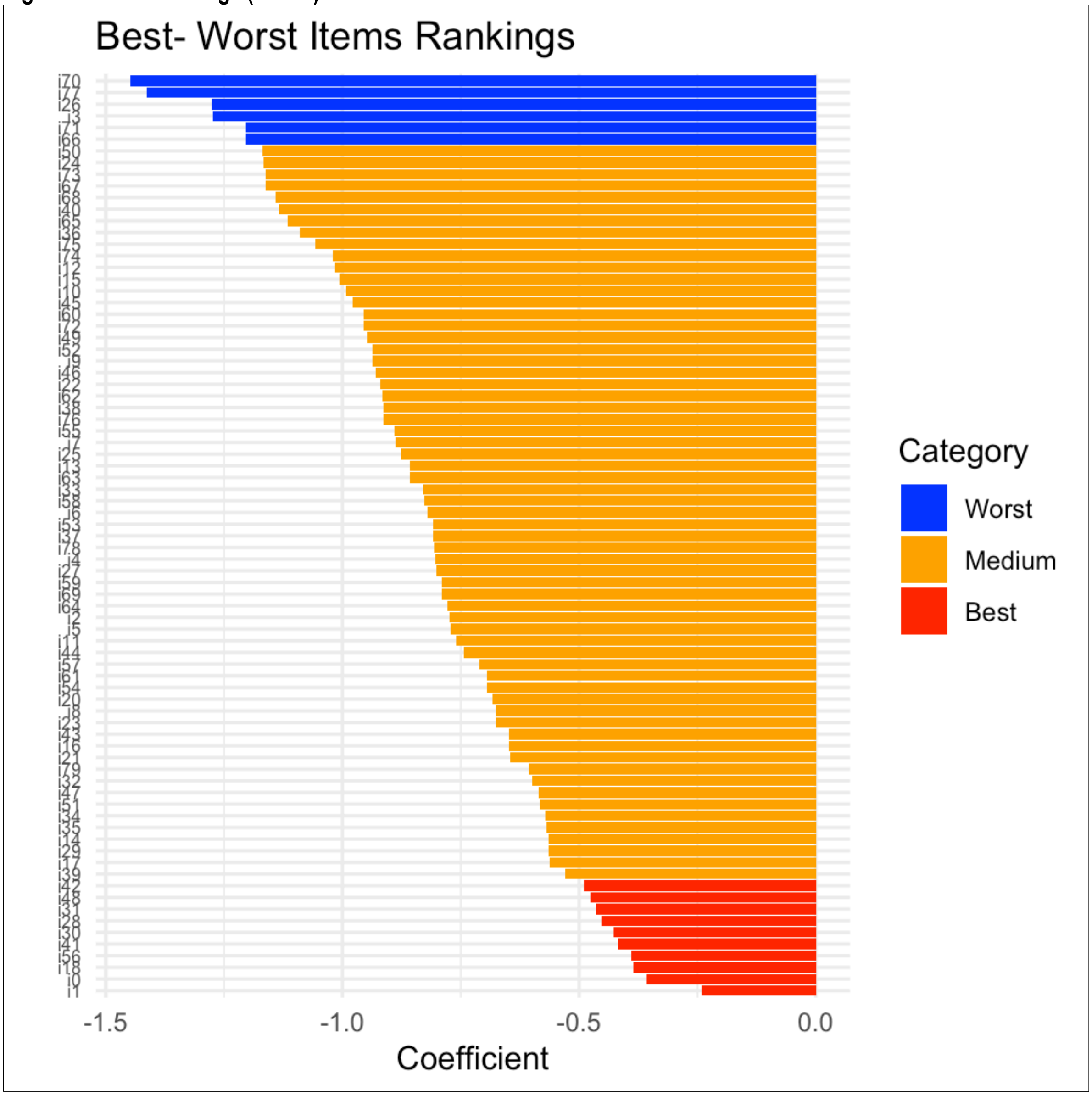
Item	Item description	Theme	Count analysis	MNL Mean (SE)
37	Assist physiotherapists, dietitians, and other allied health providers in sharing their records on My Health Record	Person-centred	0	-0.81 (0.08) ***
78	Help consumers and healthcare providers to understand and use digital health to improve care	Data-driven	0	-0.81 (0.08) ***
4	Make the use of electronic referrals, transfers of care and discharge summaries business as usual	Digitally enabled	0	-0.8 (0.07) ***
27	Make digital health literacy part of national safety and quality standards	Person-centred	0	-0.8 (0.08) ***
59	Support development of new digital health standards for emerging technologies	Inclusive	0.01	-0.79 (0.08) ***
69	Harmonise relevant policy and legislation across jurisdic-tions to support the secure use of and access to health information	Data-driven	0.01	-0.79 (0.08) ***
64	Develop analysis and governance systems to allow health data to be safely used for health research	Data-driven	0.01	-0.78 (0.08) ***
2	Assist residential aged care facilities in connecting to the online health record system, My Health Record	Digitally enabled	0.01	-0.77 (0.07) ***
5	Update healthcare provider systems to strengthen and support electronic prescribing	Digitally enabled	0.02	-0.77 (0.07) ***
11	Improve digital health skills of the health and care work-force in residential aged care facilities	Digitally enabled	0.02	-0.76 (0.08) ***
44	Develop legislation to allow health information sharing across care setting and borders	Person-centred	0.02	-0.74 (0.08) ***
57	Make it easier to share information between the health and disability systems	Inclusive	0.04	-0.71 (0.08) ***
61	Involve consumers who face barriers in using healthcare, and health and community groups, in design of digital health tools	Inclusive	0.04	-0.69 (0.08) ***
54	Develop guidelines to support the sharing of health infor-mation from personal devices with healthcare providers	Inclusive	0.04	-0.69 (0.08) ***
20	Develop a national system for online requests for blood tests and X-rays	Digitally enabled	0.05	-0.68 (0.08) ***
8	Improve and update advance care planning documents to support end-of-life decisions and ongoing care prefer-ences	Digitally enabled	0.05	-0.68 (0.08) ***
23	Improve digital systems to collect, analyse, and use data from national health registries more effectively	Digitally enabled	0.05	-0.68 (0.08) ***
43	Support secure information sharing by enhancing au-thentication services	Person-centred	0.06	-0.65 (0.08) ***
16	Modernise platforms like My Health Record to make them faster and easier to use	Digitally enabled	0.06	-0.65 (0.08) ***
21	Require new healthcare technology to work well with ex-isting systems	Digitally enabled	0.06	-0.64 (0.08) ***
79	Make clinical quality registries more accessible and able to support patient-cantered care	Data-driven	0.08	-0.61 (0.07) ***
32	Develop and deliver systems to support electronic pre-scribing and electronic medicines charts for high risk and high costs medicines	Person-centred	0.08	-0.6 (0.08) ***
47	Improve regulatory requirements to manage consent for access and use of patient health information	Person-centred	0.08	-0.59 (0.08) ***
51	Build tools to improve and expand virtual care, particu-larly for remote and rural communities	Inclusive	0.09	-0.58 (0.08) ***
34	Establish regulations for private and public healthcare providers to share information with My Health Record by default	Person-centred	0.09	-0.57 (0.08) ***
35	Add new features to My Health App to better support consumers e.g., electronic prescriptions and test results	Person-centred	0.09	-0.57 (0.08) ***

Item	Item description	Theme	Count analysis	MNL Mean (SE)
14	Make it easier for primary care providers to share information and access data	Digitally enabled	0.09	-0.57 (0.08) ***
29	Enable consumers, carers and healthcare providers to access key aged care information in My Health Record	Person-centred	0.09	-0.56 (0.08) ***
17	Create accurate terms and standardised rules to ensure systems work well across healthcare settings	Digitally enabled	0.1	-0.56 (0.08) ***
39	Connect hospital clinical information systems to the National Health Information exchange	Person-centred	0.11	-0.53 (0.08) ***
42	Automatically share information to support multidisciplinary care, including aged care and GP management plans	Person-centred	0.12	-0.49 (0.08) ***
48	Ensure provider details in health care provider directories are accurate and kept up to date	Person-centred	0.13	-0.48 (0.08) ***
31	Support clinicians and pharmacists to track and manage medicines and prescriptions in real time	Person-centred	0.13	-0.46 (0.08) ***
28	Build a system to allow real time sharing of health information safely across care settings nationally	Person-centred	0.14	-0.45 (0.08) ***
30	Enable key health information to be easily shared to support transfer of care between residential aged care and hospitals	Person-centred	0.15	-0.43 (0.08) ***
41	Improve systems to allow medicines information to be accessed and shared through My Health Record	Person-centred	0.15	-0.42 (0.08) ***
56	Create better systems to help people access mental health services	Inclusive	0.16	-0.39 (0.08) ***
18	Set standards for sharing health data with consistent rules to make it easier to share health information across systems	Digitally enabled	0.17	-0.38 (0.08) ***
0	Create secure national system for safely sharing health-related documents like clinical notes	Digitally enabled	0.17	-0.36 (0.07) ***
1	Make sure information about health care providers and health services is always current and easy to access	Digitally enabled	0.22	-0.24 (0.07) **
19	Protect Health Information and infrastructure against cyber-attacks and natural disasters	Data-driven	0.31	Base

***$p < 0.001$;

The difference in preference weights between the best or most important item and the worst or least important items is presented in Figure 7.3. The relative preference probability indicates no single initiative strongly dominates the others in terms of preference. The 95% confidence intervals (CI) were wide and overlapping across the initiatives indicating high variability in preferences among respondents (Figure A7.3, Attachment 7).

Figure 7.3: Item rankings (N=548)



Note: "The X-axis shows Coefficients: with the estimated preference score for each item, ranging from -1.5 to 0.0. The coefficients are negative because these were analyzed relative to item 19. Higher (closer to 0) values indicate more preferred items, while lower (more negative) values indicate less preferred ones."

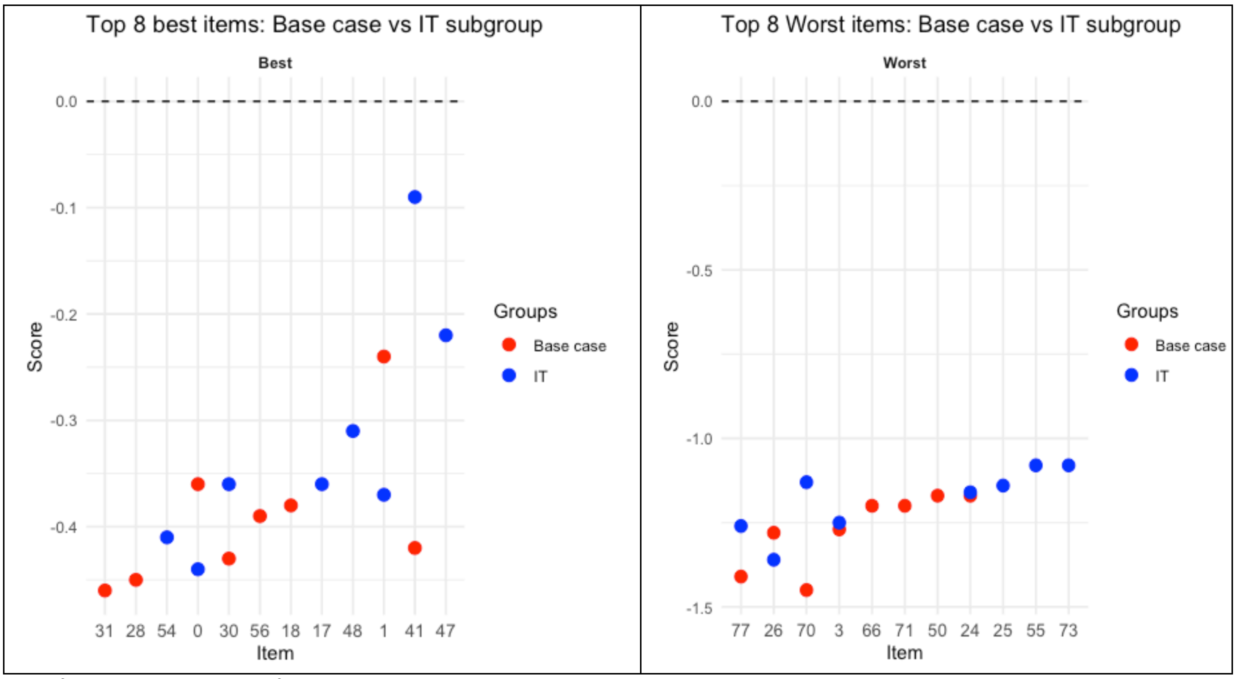
Subgroup analyses

Exploratory subgroup analyses were conducted based on respondents' gender, age, profession and education level. Of the 548 respondents who completed the survey, 19% (n=104) were health professionals (n=52) or IT professionals (n=52), which was reflective of the Australian general population. Among health professionals, the majority worked in management and administration, nursing, and allied health. Respondents were classified into seven age groups and categorised based on their education level as either lower or higher education. Educational qualifications had seven options, ranging from Year 11 and below to a postgraduate degree. For the subgroup analysis, these categories were consolidated into two groups: lower education and higher education. Of the 548 respondents, 59% (those with a diploma to a postgraduate degree) were classified as having higher education, while 41%

(those with Year 11 or below to a certificate) were classified as having lower education. The results of the subgroup analyses were largely consistent across the subgroups (Table A7.4, Attachment 7, Figure 7.4- Figure 7.7). Among IT professionals, the responses to the following items did not differ significantly from item 19 ("Protect Health Information and infrastructure against cyber-attacks and natural disasters") in statistical terms:

- 0: Create secure national system for safely sharing health-related documents like clinical notes
- 17: Create accurate terms and standardised rules to ensure systems work well across healthcare settings
- 30: Enable key health information to be easily shared to support transfer of care between residential aged care and hospitals
- 41: Improve systems to allow medicines information to be accessed and shared through My Health Record
- 47: Improve regulatory requirements to manage consent for access and use of patient health information
- 48: Ensure provider details in health care provider directories are accurate and kept up to date
- 54: Develop guidelines to support the sharing of health information from personal devices with healthcare providers

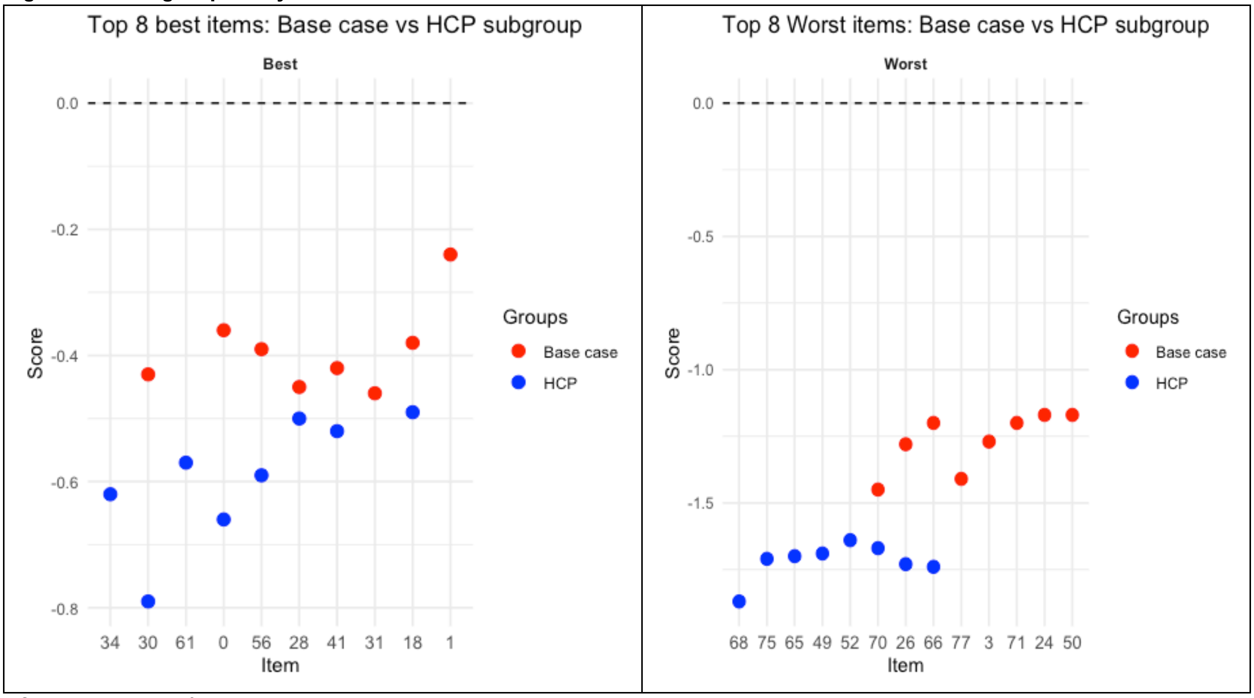
Figure 7.4: Subgroup Analysis: IT Professionals vs Base Case



IT = information technology professional

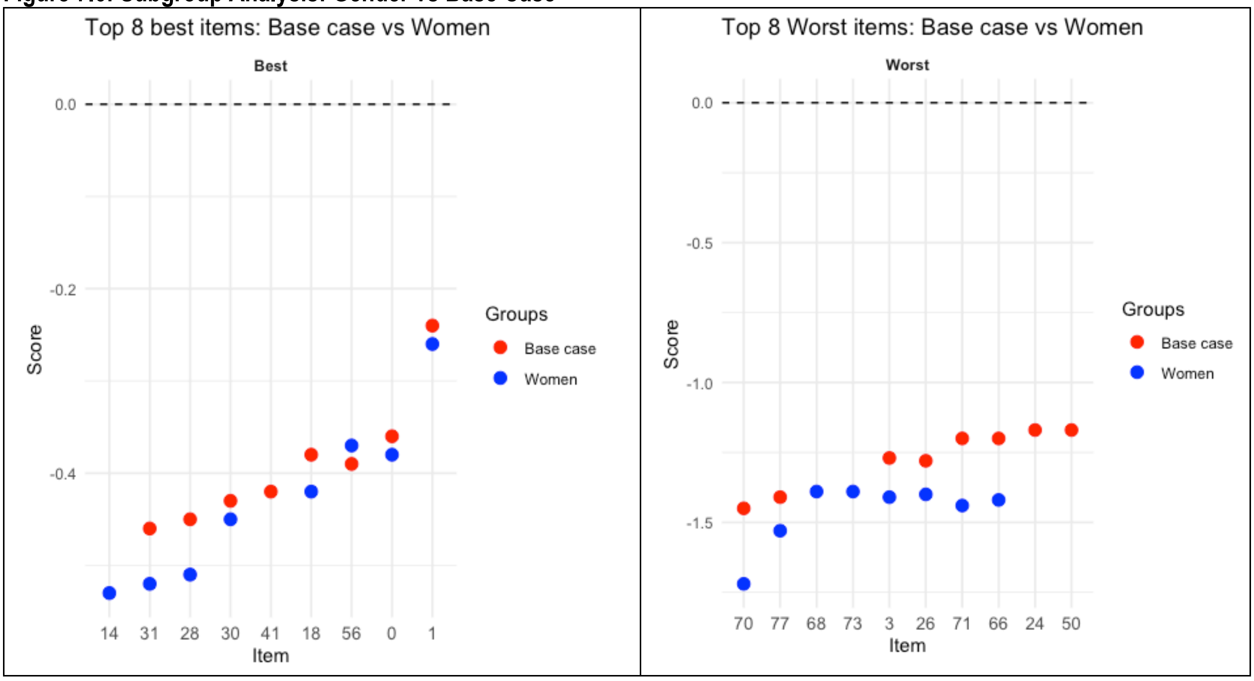
Figure 7.5: Subgroup Analysis: HCPs vs Base Case

Figure 7.5: Subgroup Analysis: HCPs vs Base Case



HCP= healthcare professionals

Figure 7.6: Subgroup Analysis: Gender vs Base Case



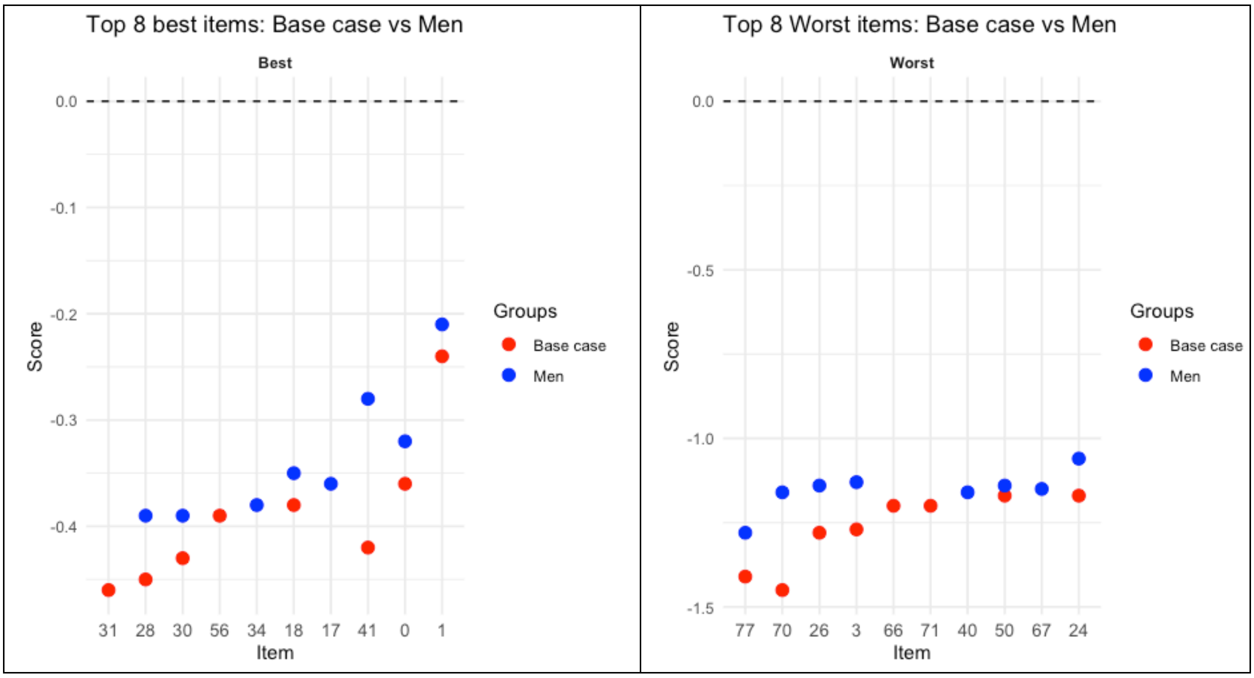
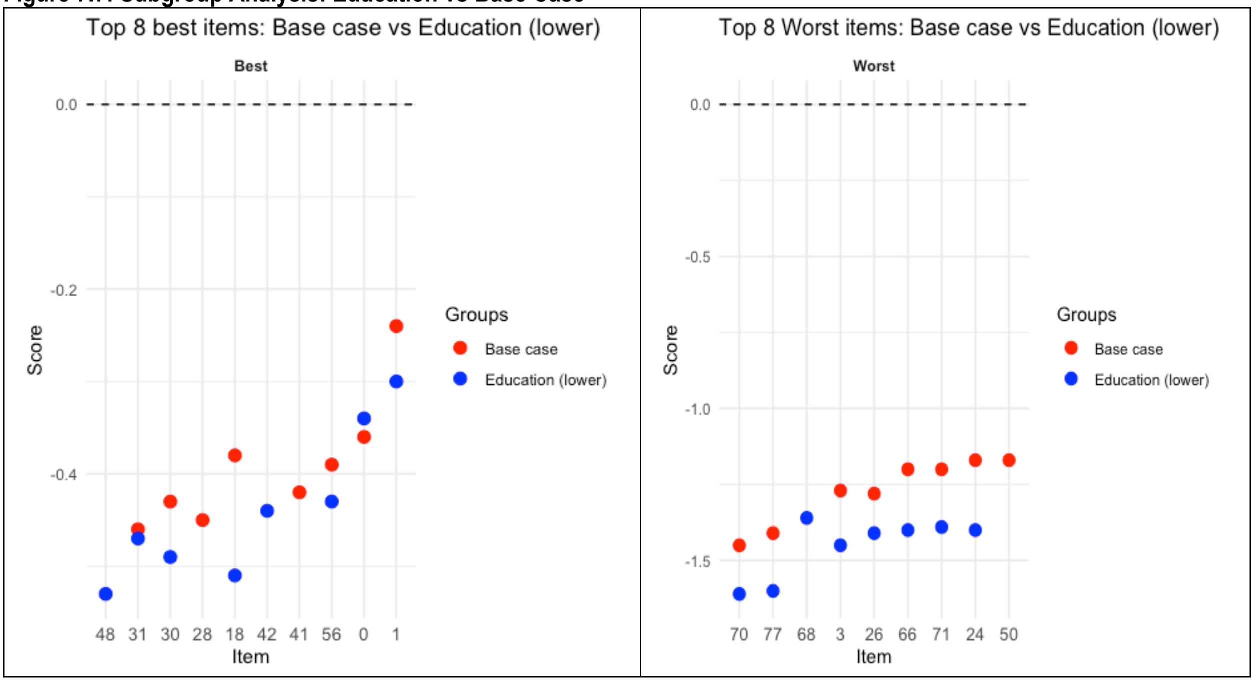
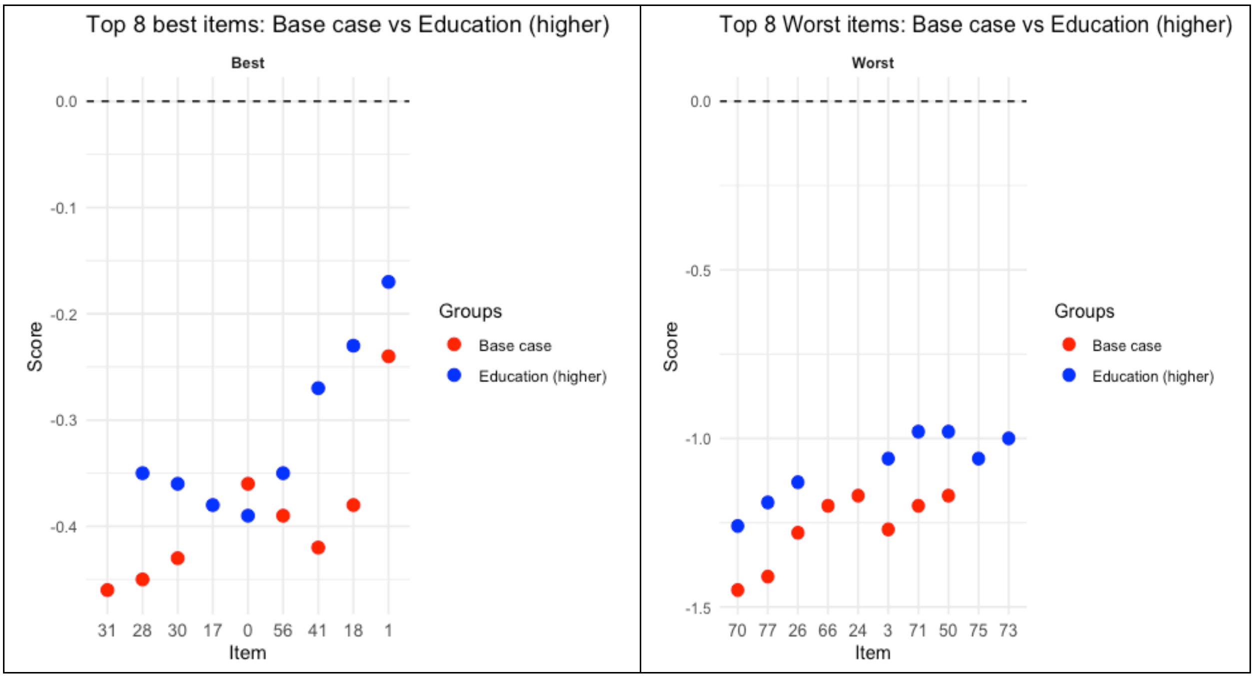


Figure 7.7: Subgroup Analysis: Education vs Base Case





Assessment of heterogeneity: Mixed logit model and latent class analysis

Two approaches were adopted to account for heterogeneity: mixed logit (MIXL) and latent class (LC) modelling. The MIXL model was estimated using the GMNL package (Sarrias and Daziano 2017) in R Studio 2024. In addition, the logitr package was used to reduce the time needed for the estimation of maximum likelihood of multinomial logit and mixed logit models (Helveston 2023). The results from the logitr analysis were obtained using 170 Sobol draws, as RStudio encountered computational limitations with higher numbers. Attempts to run the model with 175 draws failed, likely due to memory constraints or numerical instability. The final analysis was conducted with 170 draws, which successfully produced results without errors while maintaining computational feasibility. The results of the mixed logit model showed significant preference heterogeneity for most items (their standard deviation term was significantly different from zero), with the exception of five items (15, 45, 46, 76, 7) (Table 7.5). The mixed logit model, therefore, suggests that the preferences for the initiatives differ among respondents.

Table 7.5: Results of mixed logit model (N=548)

Item	Description	Mean (SE)	SD (SE)
70	Get ready for new technologies like AI and genomics in healthcare	-1.86 (0.11) ***	1.56 (0.14) ***
77	Participate in evaluations and provide feedback on experiences of digital health	-1.77 (0.1) ***	0.73 (0.17) ***
3	Roll out a national newborn enrolment system that connects to government services	-1.6 (0.11) ***	1.3 (0.14) ***
26	Undertake research on the effectiveness of digital health literacy programs	-1.58 (0.1) ***	1.01 (0.14) ***
66	Australia to cooperate internationally to improve secure digital health systems	-1.51 (0.11) ***	1.45 (0.14) ***

Item	Description	Mean (SE)	SD (SE)
71	Improve national and local digital health systems to allow for use of AI, machine learning, and genomics	-1.5 (0.1) ***	-1.21 (0.14) ***
73	Identify healthcare opportunities and risks arising from whole-of economy approaches to regulating AI	-1.49 (0.11) ***	1.49 (0.14) ***
67	Ensure Aboriginal and Torres Strait Islander communities can access data held by government and other relevant entities to support local decision making	-1.46 (0.11) ***	-1.66 (0.14) ***
24	Involve consumers in the design and delivery of digital health literacy programs	-1.45 (0.1) ***	-1.14 (0.14) ***
50	Evaluate virtual care and policy tools that support team based multidisciplinary care.	-1.44 (0.09) ***	-0.44 (0.22) .
68	Support the use of exploratory and simulation research activities to evaluate digital health solutions	-1.41 (0.1) ***	-0.61 (0.18) ***
40	Allow pregnancy and child health information to be shared and accessed through national digital systems	-1.41 (0.1) ***	0.8 (0.15) ***
65	Australia to take part in discussion to harmonise global health technology standards and products and to reduce costs	-1.4 (0.11) ***	1.61 (0.14) ***
36	Involve consumers in improving tools like My Health Record and My Health App	-1.35 (0.1) ***	-1.03 (0.14) ***
75	Help set up systems for sharing data like genomics and for My Health Record	-1.29 (0.09) ***	-0.67 (0.16) ***
12	Develop guidelines and resources for digital health learning, education and practice	-1.25 (0.09) ***	-0.53 (0.19) **
15	Build digital tools that support healthcare providers in their training and career paths	-1.24 (0.09) ***	0.06 (0.46)
74	Support and regulate use of new medical technology including bioinformatics, AI and mixed reality in healthcare settings	-1.24 (0.1) ***	-1.35 (0.14) ***
10	Develop a framework to help organisations ensure their health workforce is digital health ready	-1.24 (0.09) ***	-0.52 (0.19) **
45	Implement systems to store and manage healthcare provider details	-1.2 (0.09) ***	0.11 (0.43)
72	Monitor and identify emerging data sources and technology that support healthcare	-1.17 (0.09) ***	-0.66 (0.17) ***
52	Develop and design ways to support the sharing of health information from personal devices	-1.17 (0.09) ***	0.56 (0.18) **
49	Provide digital tools to support expanded delivery of home-based care	-1.17 (0.09) ***	0.66 (0.17) ***
60	Align digital health plans and activities across national, state, territory Closing the Gap Implementation Plans	-1.17 (0.09) ***	-0.86 (0.15) ***
9	Implement the National Digital Health Capability Action Plan	-1.15 (0.09) ***	0.48 (0.21) *
46	Progress integration between the national digital identity solution and healthcare systems	-1.14 (0.09) ***	0.06 (0.29)
76	Measure, monitor and report on changes in digital health to help plan for the future	-1.13 (0.09) ***	-0.27 (0.36)
22	Require electronic prescribing for expensive or high-risk medicines by updating technology and rules	-1.12 (0.1) ***	-1.02 (0.14) ***
38	Implement unique national healthcare identifiers for individuals and healthcare providers	-1.11 (0.09) ***	-0.56 (0.19) **
62	Research and share information about digital health care to help translate new models into clinical practice	-1.11 (0.09) ***	-0.6 (0.18) ***
55	Create rules and plans to safely use personal devices for sharing health information	-1.09 (0.09) ***	-0.86 (0.15) ***
7	Standardise clinical information systems for residential aged care facilities	-1.09 (0.09) ***	0 (0.2)
25	Work with consumers to design health tools that are easy to use and accessible	-1.08 (0.1) ***	1.01 (0.14) ***

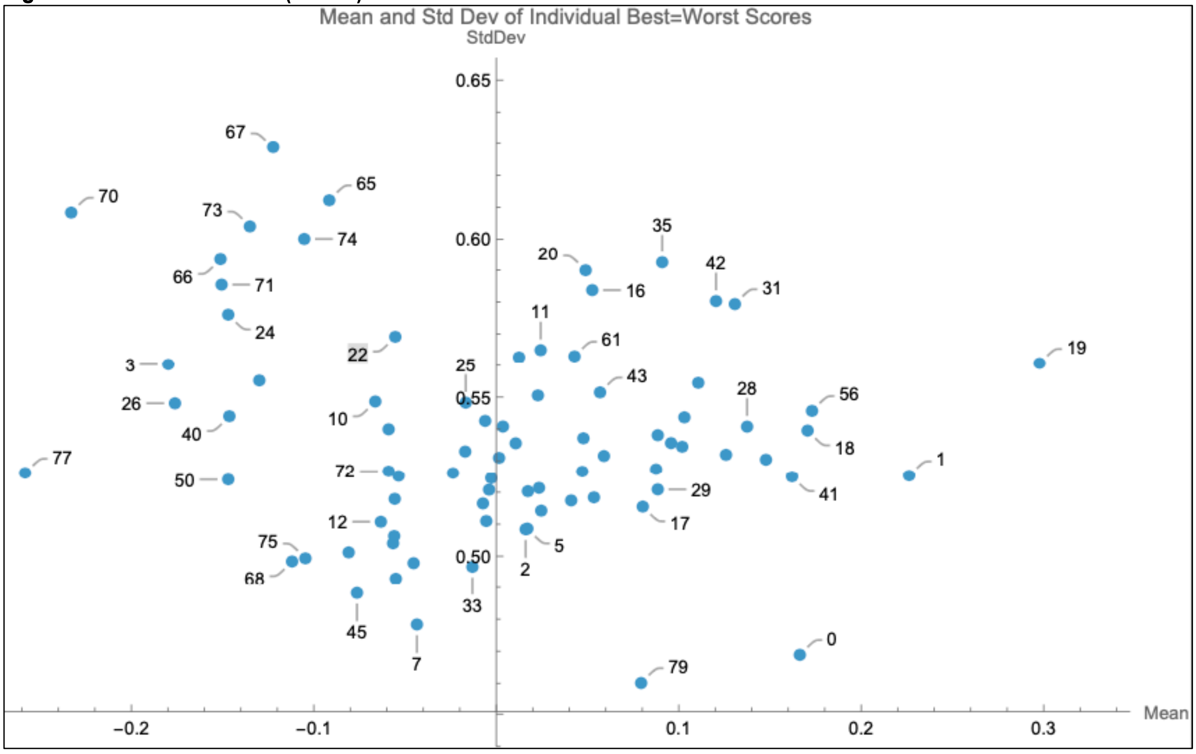
Item	Description	Mean (SE)	SD (SE)
13	Create an online platform to share and connect digital resources for the health workforce	-1.06 (0.09) ***	0.63 (0.17) ***
63	Collect and share patient reported experience and outcomes data to improve healthcare	-1.04 (0.09) ***	0.8 (0.15) ***
6	Help aged care software developers to align with My Health Record and the Aged Care Transfer Summary	-1.02 (0.09) ***	0.74 (0.15) ***
33	Develop and expand operational support for electronic prescribing including incident management support	-1.02 (0.09) ***	0.59 (0.18) ***
58	Improve digital tools to support team-based care for people registered with MyMedicare	-1.01 (0.09) ***	-0.82 (0.15) ***
78	Help consumers and healthcare providers to understand and use digital health to improve care	-1 (0.1) ***	-1.01 (0.14) ***
53	Create systems that let healthcare providers to collect and display health information from personal devices securely	-1 (0.09) ***	0.91 (0.14) ***
37	Assist physiotherapists, dietitians, and other allied health providers in sharing their records on My Health Record	-0.98 (0.1) ***	-1.07 (0.14) ***
4	Make the use of electronic referrals, transfers of care and discharge summaries business as usual	-0.98 (0.09) ***	-1.12 (0.13) ***
27	Make digital health literacy part of national safety and quality standards	-0.97 (0.09) ***	-0.76 (0.16) ***
69	Harmonise relevant policy and legislation across jurisdictions to support the secure use of and access to health information	-0.96 (0.09) ***	0.86 (0.15) ***
2	Assist residential aged care facilities in connecting to the online health record system, My Health Record	-0.96 (0.09) ***	-0.67 (0.16) ***
64	Develop analysis and governance systems to allow health data to be safely used for health research	-0.96 (0.09) ***	0.59 (0.17) ***
59	Support development of new digital health standards for emerging technologies	-0.96 (0.09) ***	0.55 (0.19) **
5	Update healthcare provider systems to strengthen and support electronic prescribing	-0.94 (0.09) ***	0.38 (0.24)
11	Improve digital health skills of the health and care workforce in residential aged care facilities	-0.93 (0.09) ***	0.62 (0.17) ***
44	Develop legislation to allow health information sharing across care setting and borders	-0.9 (0.09) ***	0.56 (0.17) ***
54	Develop guidelines to support the sharing of health information from personal devices with healthcare providers	-0.85 (0.09) ***	-0.75 (0.16) ***
57	Make it easier to share information between the health and disability systems	-0.85 (0.09) ***	0.89 (0.14) ***
20	Develop a national system for online requests for blood tests and X-rays	-0.85 (0.1) ***	1.16 (0.14) ***
61	Involve consumers who face barriers in using healthcare, and health and community groups, in design of digital health tools	-0.84 (0.09) ***	-0.94 (0.14) ***
8	Improve and update advance care planning documents to support end-of-life decisions and ongoing care preferences	-0.83 (0.09) ***	-0.73 (0.16) ***
23	Improve digital systems to collect, analyse, and use data from national health registries more effectively	-0.83 (0.09) ***	0.64 (0.17) ***
21	Require new healthcare technology to work well with existing systems	-0.81 (0.09) ***	-0.71 (0.16) ***
16	Modernise platforms like My Health Record to make them faster and easier to use	-0.8 (0.1) ***	-1.27 (0.13) ***
43	Support secure information sharing by enhancing authentication services	-0.79 (0.09) ***	-0.98 (0.14) ***
79	Make clinical quality registries more accessible and able to support patient-cantered care	-0.73 (0.09) ***	-0.46 (0.21) *
51	Build tools to improve and expand virtual care, particularly for remote and rural communities	-0.72 (0.09) ***	-0.99 (0.14) ***

Item	Description	Mean (SE)	SD (SE)
32	Develop and deliver systems to support electronic prescribing and electronic medicines charts for high risk and high costs medicines	-0.7 (0.09) ***	0.94 (0.14) ***
47	Improve regulatory requirements to manage consent for access and use of patient health information	-0.7 (0.09) ***	0.75 (0.16) ***
34	Establish regulations for private and public healthcare providers to share information with My Health Record by default	-0.7 (0.1) ***	-1.1 (0.14) ***
14	Make it easier for primary care providers to share information and access data	-0.7 (0.09) ***	0.94 (0.14) ***
29	Enable consumers, carers and healthcare providers to access key aged care information in My Health Record	-0.69 (0.09) ***	0.83 (0.15) ***
17	Create accurate terms and standardised rules to ensure systems work well across healthcare settings	-0.68 (0.09) ***	-0.62 (0.19) ***
35	Add new features to My Health App to better support consumers e.g., electronic prescriptions and test results	-0.66 (0.1) ***	-1.42 (0.14) ***
39	Connect hospital clinical information systems to the National Health Information exchange	-0.64 (0.09) ***	-0.75 (0.16) ***
42	Automatically share information to support multidisciplinary care, including aged care and GP management plans	-0.58 (0.1) ***	-1.15 (0.14) ***
48	Ensure provider details in health care provider directories are accurate and kept up to date	-0.58 (0.09) ***	-0.56 (0.19) **
28	Build a system to allow real time sharing of health information safely across care settings nationally	-0.56 (0.09) ***	0.98 (0.14) ***
31	Support clinicians and pharmacists to track and manage medicines and prescriptions in real time	-0.56 (0.09) ***	-1.09 (0.14) ***
41	Improve systems to allow medicines information to be accessed and shared through My Health Record	-0.49 (0.09) ***	0.58 (0.19) **
30	Enable key health information to be easily shared to support transfer of care between residential aged care and hospitals	-0.49 (0.09) ***	-0.77 (0.16) ***
18	Set standards for sharing health data with consistent rules to make it easier to share health information across systems	-0.45 (0.09) ***	0.94 (0.15) ***
56	Create better systems to help people access mental health services	-0.44 (0.09) ***	0.86 (0.15) ***
0	Create secure national system for safely sharing health-related documents like clinical notes	-0.41 (0.09) ***	0.81 (0.14) ***
1	Make sure information about health care providers and health services is always current and easy to access	-0.27 (0.09) **	-0.98 (0.14) ***
19	Protect Health Information and infrastructure against cyber-attacks and natural disasters	Base	

*** p=0, ** p=0.001, * p=0.01, . p=0.05

An overview of prioritisation of items in the BWS by individual respondents is presented in Figure 7.8. Each individual's BWS score for an item is derived by subtracting the number of times it was chosen as worst from the number of times it was chosen as best. These scores reflect the relative importance or preference assigned to different digital health initiatives. The scatter plot of mean and standard deviation values, illustrates the variation in individual preferences and consistency across the sample. The data shows clear prioritisation of certain items with positive means, particularly 19, 1, and 0) while others face consistent rejection (items 77, 70, 3 and 26). The varying standard deviations highlight where consensus exists versus where opinions remain divided. The distinctive spread of items indicates that respondents held defined preferences rather than neutral positions, offering clear direction for strategic prioritisation of digital health resources and focus areas.

Figure 7.8: Individual BWS (N=548)



A Pearson's Chi-squared test was conducted to examine whether the frequency of 'best' and 'worst' selections differed by item position within the choice tasks (positions 1 to 5). The results revealed a significant deviation from the expected uniform distribution across positions (χ^2 = 306.29, df = 4, p < 0.001). The largest contribution to the test statistic came from position 5, which accounted for over 56% of the total χ^2 value, indicating that items presented in this position were selected disproportionately more often as 'worst' and less often as 'best' (Table 7.6). These findings suggest that the position of an item within the choice task may have influenced respondent selections, potentially reflecting position-related bias in the responses. Randomisation of item order within choice tasks was employed to minimise potential ordering effects and reduce bias in respondents' selections.

Table 7.6: Pearson's Chi-squared test results: items position within the choice tasks (N=548)

Item	Best (Observed)	Worst (Observed)	Expected (Both)	Std. Residual (Best)	Std. Residual (Worst)	Contribution to χ^2 (%)
1	3094	2677	2885.5	4.0	-4.0	4.92
2	3309	2687	2998.0	6.0	-6.0	10.53
3	3066	2731	2898.5	3.0	-3.0	3.16
4	2740	3079	2909.5	-3.0	3.0	3.22
5	2587	3622	3104.5	-9.0	9.0	28.16

Latent class analysis

Latent-class analysis (LCA) allows for identifying distinct preference groups that may not cluster according to sociodemographic characteristics. LCA is used to identify unobserved subgroups within a population based on individuals' responses or preferences. It models heterogeneity by assuming that the population consists of a finite number of latent (i.e., unobserved) classes, each characterised by its own distinct probability distribution. Rather than assuming a continuous distribution of preferences, LCA assumes that the diversity in responses can be captured by a discrete number of distinct segments or classes (Hensher et al. 2018). Latent class analysis can identify key populations with unique needs and wants, give insight into these groups' relative sizes, and ultimately indicate whether multiple tailored strategies may be required to maximise reach and adoption.

To decide on the optimal number of classes the model was estimated with varying number of classes, from 2 up to 6. The selection of the optimal number of classes was guided by AIC and BIC statistics (Table 7.7), as well as by assessing the reasonableness of the results with different class numbers (Train 2009). Dziak et al. have shown that BIC is the preferred statistical criterion in this context (Dziak et al. 2020). The latent class analysis yielded consistency regarding the optimal number of classes across different statistical packages, confirming the robustness of our class structure determination. However, notable differences emerged in the fit statistics, with the Latent Gold software generating higher log likelihood values and AIC and BIC metrics across various class solutions compared to equivalent analyses conducted in RStudio and Stata. This divergence in fit statistics between software implementations, despite agreement on class enumeration, suggests potential variations in algorithmic approaches or estimation procedures.

Table 7.7: Models goodness of fit statistics

Classes	Parameters	Log-likelihood	AIC	BIC
RStudio output				
2	14796	-42780	85877	87086
3	14796	-42610	85697	87514
4	14796	-42374	85385	87810
5	14796	-42250	85298	88331
6	14796	-42101	85160	88802
Stata output				
2	14796	-42780	85877	86562
3	14796	-42550	85577	86607
4	14796	-42356	86725	87044
5	14796	-42217	85231	86950
6	14796	-42100	85158	87220
Latent gold output				
2	14796	-38211	76821	77678
3	14796	-38094	76786	78073
4	14796	-37898	76593	78312
5	14796	-37769	76535	78684
6	14796	-37861	76921	79500

AIC= Akaike Information Criterion, BIC= Bayesian Information Criterion

The results from the three approaches for the LCA with 2 classes are presented in Table 7.8. The model includes a set of MNL model coefficients for each of the two classes and a class probability function indicating the probability of class membership. The Latent Class Analysis identified two groups with broadly similar preferences toward digital health initiatives, with both Class 1 (65.05%) and Class 2 (34.95%) ranking items 0, 1, and 18 among the highest. These items, focused on secure document sharing, accessible provider information, and data interoperability standards, reflect support for strengthening foundational digital infrastructure. Similarly, both classes consistently ranked items 77, 70, 66, 3, and 26 among the lowest, suggesting limited perceived value in participatory evaluation, AI/genomics readiness, international cooperation, newborn enrolment systems, and digital literacy research (Table 7.8).

Some differences emerged in specific priorities. Class 2 placed items 28, 32, and 35 among its top five—indicating stronger support for real-time information sharing, advanced e-prescribing, and en-hanced consumer tools. In contrast, Class 1 prioritised Items 17 and 47, focused on standardisation and consent management, pointing to a stronger emphasis on regulatory and governance structures. In terms of least-preferred initiatives, Class 2 included Item 65 (global standards harmonisation), while Class 1 ranked Items 40 (maternal and child health data sharing) and 75 (genomics data systems) among its lowest. These differences indicate distinct subgroup priorities, with Class 2 more focused on consumer-facing and advanced digital capabilities, and Class 1 more concerned with foundational rules and oversight. The results were consistent in terms of ordering of the items across the three software packages, which validate the robustness of the latent class analysis, though some minor differences in coefficient values can be observed (Table A7.3, Appendix 7).

Table 7.8: Latent class logit results: model with 2 classes (N=548)

Item	Description	Class 1 (Mean, SE)	Class 2 (Mean, SE)
		65.05%	34.95%
0	Create secure national system for safely sharing health-related documents like clinical notes	-0.37 (0.09) ***	-0.38 (0.14) **
1	Make sure information about health care providers and health services is always current and easy to access	-0.26 (0.09) **	-0.21 (0.15)
2	Assist residential aged care facilities in connecting to the online health record system, My Health Record	-0.75 (0.09) ***	-0.89 (0.15) ***
3	Roll out a national newborn enrolment system that connects to government services	-0.98 (0.1) ***	-2 (0.16) ***
4	Make the use of electronic referrals, transfers of care and discharge summaries business as usual	-0.69 (0.09) ***	-1.11 (0.15) ***
5	Update healthcare provider systems to strengthen and support electronic prescribing	-0.78 (0.1) ***	-0.84 (0.15) ***
6	Help aged care software developers to align with My Health Record and the Aged Care Transfer Summary	-0.57 (0.09) ***	-1.42 (0.15) ***
7	Standardise clinical information systems for residential aged care facilities	-0.72 (0.1) ***	-1.32 (0.15) ***
8	Improve and update advance care planning documents to support end-of-life decisions and ongoing care preferences	-0.6 (0.1) ***	-0.91 (0.15) ***
9	Implement the National Digital Health Capability Action Plan	-0.72 (0.1) ***	-1.48 (0.15) ***
10	Develop a framework to help organisations ensure their health workforce is digital health ready	-0.7 (0.1) ***	-1.69 (0.15) ***
11	Improve digital health skills of the health and care workforce in residential aged care facilities	-0.51 (0.1) ***	-1.34 (0.15) ***
12	Develop guidelines and resources for digital health learning, education and practice	-0.58 (0.1) ***	-2.02 (0.15) ***
13	Create an online platform to share and connect digital resources for the health workforce	-0.66 (0.1) ***	-1.36 (0.15) ***
14	Make it easier for primary care providers to share information and access data	-0.63 (0.1) ***	-0.49 (0.15) ***
15	Build digital tools that support healthcare providers in their training and career paths	-0.76 (0.1) ***	-1.62 (0.15) ***
16	Modernise platforms like My Health Record to make them faster and easier to use	-0.59 (0.1) ***	-0.83 (0.15) ***
17	Create accurate terms and standardised rules to ensure systems work well across healthcare settings	-0.38 (0.1) ***	-1.03 (0.15) ***
18	Set standards for sharing health data with consistent rules to make it easier to share health information across systems	-0.25 (0.1) **	-0.7 (0.15) ***
19	Protect Health Information and infrastructure against cyber-attacks and natural disasters	Base level	Base level
20	Develop a national system for online requests for blood tests and X-rays	-0.73 (0.1) ***	-0.66 (0.15) ***

Item	Description	Class 1 (Mean, SE)	Class 2 (Mean, SE)
		65.05%	34.95%
21	Require new healthcare technology to work well with existing systems	-0.48 (0.1) ***	-1.06 (0.15) ***
22	Require electronic prescribing for expensive or high-risk medicines by updating technology and rules	-0.68 (0.1) ***	-1.5 (0.15) ***
23	Improve digital systems to collect, analyse, and use data from national health registries more effectively	-0.42 (0.1) ***	-1.26 (0.15) ***
24	Involve consumers in the design and delivery of digita health literacy programs	-0.77 (0.1) ***	-2.08 (0.15) ***
25	Work with consumers to design health tools that are easy to use and accessible	-0.55 (0.1) ***	-1.65 (0.15) ***
26	Undertake research on the effectiveness of digital health literacy programs	-0.77 (0.1) ***	-2.43 (0.16) ***
27	Make digital health literacy part of national safety and quality standards	-0.43 (0.1) ***	-1.63 (0.15) ***
28	Build a system to allow real time sharing of health information safely across care settings nationally	-0.55 (0.1) ***	-0.28 (0.15) .
29	Enable consumers, carers and healthcare providers to access key aged care information in My Health Record	-0.53 (0.1) ***	-0.71 (0.15) ***
30	Enable key health information to be easily shared to support transfer of care between residential aged care and hospitals	-0.45 (0.1) ***	-0.42 (0.15) **
31	Support clinicians and pharmacists to track and manage medicines and prescriptions in real time	-0.55 (0.1) ***	-0.3 (0.15) .
32	Develop and deliver systems to support electronic prescribing and electronic medicines charts for high risk and high costs medicines	-0.45 (0.1) ***	-0.96 (0.15) ***
33	Develop and expand operational support for electronic prescribing including incident management support	-0.65 (0.1) ***	-1.31 (0.15) ***
34	Establish regulations for private and public healthcare providers to share information with My Health Record by default	-0.5 (0.1) ***	-0.78 (0.15) ***
35	Add new features to My Health App to better support consumers e.g., electronic prescriptions and test results	-0.73 (0.1) ***	-0.3 (0.15) .
36	Involve consumers in improving tools like My Health Record and My Health App	-0.82 (0.1) ***	-1.74 (0.16) ***
37	Assist physiotherapists, dietitians, and other allied health providers in sharing their records on My Health Record	-0.76 (0.1) ***	-0.93 (0.15) ***
38	Implement unique national healthcare identifiers for individuals and healthcare providers	-0.7 (0.1) ***	-1.45 (0.15) ***
39	Connect hospital clinical information systems to the National Health Information exchange	-0.55 (0.1) ***	-0.51 (0.15) ***
40	Allow pregnancy and child health information to be shared and accessed through national digital systems	-0.9 (0.1) ***	-1.72 (0.16) ***
41	Improve systems to allow medicines information to be accessed and shared through My Health Record	-0.44 (0.1) ***	-0.42 (0.15) **
42	Automatically share information to support multidisciplinary care, including aged care and GP managemen plans	-0.56 (0.1) ***	-0.41 (0.15) **
43	Support secure information sharing by enhancing authentication services	-0.51 (0.09) ***	-1 (0.15) ***
44	Develop legislation to allow health information sharing across care setting and borders	-0.63 (0.1) ***	-1.05 (0.15) ***
45	Implement systems to store and manage healthcare provider details	-0.8 (0.1) ***	-1.43 (0.15) ***

Item	Description	Class 1 (Mean, SE)	Class 2 (Mean, SE)
		65.05%	34.95%
46	Progress integration between the national digital identity solution and healthcare systems	-0.73 (0.1) ***	-1.46 (0.15) ***
47	Improve regulatory requirements to manage consent for access and use of patient health information	-0.4 (0.1) ***	-1.04 (0.15) ***
48	Ensure provider details in health care provider directories are accurate and kept up to date	-0.45 (0.1) ***	-0.58 (0.15) ***
49	Provide digital tools to support expanded delivery of home-based care	-0.77 (0.1) ***	-1.42 (0.15) ***
50	Evaluate virtual care and policy tools that support team based multidisciplinary care.	-0.8 (0.1) ***	-2.05 (0.15)***
51	Build tools to improve and expand virtual care, particularly for remote and rural communities	-0.46 (0.1) ***	-0.92 (0.15)***
52	Develop and design ways to support the sharing of health information from personal devices	-0.63 (0.1) ***	-1.68 (0.15)***
53	Create systems that let healthcare providers to collect and display health information from personal devices securely	-0.62 (0.1) ***	-1.29 (0.15)***
54	Develop guidelines to support the sharing of health information from personal devices with healthcare providers	-0.44 (0.1) ***	-1.27 (0.15)***
55	Create rules and plans to safely use personal devices for sharing health information	-0.74 (0.1) ***	-1.29 (0.15)***
56	Create better systems to help people access mental health services	-0.4 (0.1) ***	-0.42 (0.15)**
57	Make it easier to share information between the health and disability systems	-0.72 (0.1) ***	-0.77 (0.15)***
58	Improve digital tools to support team-based care for people registered with MyMedicare	-0.66 (0.1) ***	-1.25 (0.15)***
59	Support development of new digital health standards for emerging technologies	-0.48 (0.1) ***	-1.5 (0.15)***
60	Align digital health plans and activities across national state, territory Closing the Gap Implementation Plans	-0.81 (0.1) ***	-1.36 (0.15)***
61	Involve consumers who face barriers in using healthcare, and health and community groups, in design of digital health tools	-0.48 (0.1) ***	-1.2 (0.15)***
62	Research and share information about digital health care to help translate new models into clinical practice	-0.59 (0.1) ***	-1.67 (0.15)***
63	Collect and share patient reported experience and outcomes data to improve healthcare	-0.6 (0.1) ***	-1.48 (0.15)***
64	Develop analysis and governance systems to allow health data to be safely used for health research	-0.52 (0.1) ***	-1.39 (0.15)***
65	Australia to take part in discussion to harmonise global health technology standards and products and to reduce costs	-0.56 (0.1) ***	-2.37 (0.15)***
66	Australia to cooperate internationally to improve secure digital health systems	-0.54 (0.1) ***	-2.69 (0.17)***
67	Ensure Aboriginal and Torres Strait Islander communities can access data held by government and other relevant entities to support local decision making	-0.8 (0.1) ***	-2.02 (0.16)***
68	Support the use of exploratory and simulation research activities to evaluate digital health solutions	-0.73 (0.1) ***	-2.1 (0.15)***
69	Harmonise relevant policy and legislation across jurisdictions to support the secure use of and access to health information	-0.6 (0.1) ***	-1.26 (0.14)***
70	Get ready for new technologies like AI and genomics in healthcare	-0.95 (0.1) ***	-2.62 (0.16)***

Item	Description	Class 1 (Mean, SE)	Class 2 (Mean, SE)
		65.05%	34.95%
71	Improve national and local digital health systems to allow for use of AI, machine learning, and genomics	-0.72 (0.1) ***	-2.29 (0.16)***
72	Monitor and identify emerging data sources and technology that support healthcare	-0.59 (0.1) ***	-1.81 (0.15)***
73	Identify healthcare opportunities and risks arising from whole-of economy approaches to regulating AI	-0.79 (0.1) ***	-2.04 (0.15)***
74	Support and regulate use of new medical technology including bioinformatics, AI and mixed reality in healthcare settings	-0.62 (0.1) ***	-1.94 (0.15)***
75	Help set up systems for sharing data like genomics and for My Health Record	-0.86 (0.09) ***	-1.58 (0.15)***
76	Measure, monitor and report on changes in digital health to help plan for the future	-0.63 (0.1) ***	-1.6 (0.15)***
77	Participate in evaluations and provide feedback on experiences of digital health	-0.97 (0.1) ***	-2.45 (0.15)***
78	Help consumers and healthcare providers to understand and use digital health to improve care	-0.6 (0.1) ***	-1.32 (0.15)***
79	Make clinical quality registries more accessible and able to support patient-cantered care	-0.47 (0.09) ***	-0.95 (0.14)***

*** p=0, ** p=0.001, * p=0.01, . p=0.05

Latent class membership was examined in relation to respondents' demographic characteristics to support interpretation and potential implementation relevance. Respondents in Classes 1 were relatively younger than the respondents in Class 2 (Table 7.9). Diagnostic tests of class assignment indicated good separation between classes, as reflected in the posterior class membership probabilities.

Table 7.9: Respondents characteristics in the LCA

Respondent characteristic	Class 1 (N=360)	Class 2 (N=188)
Age (n, %)		
18-24	44 (13)	10 (6)
25-34	82 (23)	17 (10)
35-44	73 (21)	23 (13)
45-54	60 (17)	31 (17)
55-64	43 (13)	40 (22)
65-74	36 (11)	52 (28)
75+	19 (6)	15 (8)
Gender (n, %)		
Men	184 (52)	81 (44)
Women	175 (49)	107 (57)
Other	1 (1)	0 (0)

Feedback responses

The responses to the post-BWS choice task questions are presented in Table 7.10. The results indicate that most respondents did not find it difficult to differentiate between the items and considered all the available options. However, 50% of respondents felt that there were too many tasks, a concern substantiated by the notably extended average completion time (28 min, SD 83 min). This pattern suggests that survey fatigue may have influenced response quality and highlights the need to consider respondent burden in future study designs.

Table 7.10: Post survey questions (N=548)

	Respondents, n (%) (N=548)
Difficult to tell the difference between the options presented	
Strongly disagree (1)	57 (10)
Disagree (2)	164 (30)
Neither agree nor disagree (3)	131 (24)
Agree (4)	161 (29)
Strongly Agree (5)	35 (6)
Considered all the options	
Strongly disagree (1)	2 (0)
Disagree (2)	14 (3)
Neither agree nor disagree (3)	44 (8)
Agree (4)	260 (47)
Strongly Agree (5)	228 (42)
Task number	
Just right	261 (48)
Too few	13 (2)
Too many	210 (38)
Way too many	64 (12)

The results of the question about respondents' attitude to technology and innovation are presented in Table 7.11. The data shows that while response rates for these items were low, the majority of those who did respond self-identified as technology curious.

Table 7.11: Attitudinal questions

Approach to technology and innovation	**Respondents, n (%) (N=104)[a]**
Early adopter	2 (2)
Neutral	6 (6)
Reluctant	1 (<1)
Sceptical	2 (2)
Technology curious	10 (10)

Note:

a. question about respondents' approach to technology was presented to a subset of respondents who identified as healthcare or IT professionals

Discussion

Digital transformation is becoming increasingly vital in the healthcare sector, as DHTs offer promising solutions to enhance service delivery and address persistent challenges such as an ageing population, limited access to healthcare professionals, and rising costs of care. However, the successful implementation and adoption of DHTs require significant investment that extends beyond the technologies themselves. This includes strengthening organisational capabilities, upgrading information systems, and developing skilled human resources. Evaluating digital health maturity plays a crucial role in this process by providing insights into an organisation's capacity across multiple dimensions, from business processes and organisational structures to information systems and workforce readiness (Woods et al. 2022). In this context, digital health strategies serve as structured roadmaps that help prioritise initiatives most likely to drive effective and sustainable digital transformation.

BWS studies hold significant potential to influence policy due to their focus on prioritisation (Hollin 2020). Policymakers often face the challenge of weighing competing policy options and prioritising certain issues within healthcare. This process frequently involves making decisions among stakeholders with differing goals. By asking respondents to select both the most and least important items within a set, BWS captures priorities and provides a quantifiable measure of relative preferences, minimising cognitive biases associated with traditional rating or ranking methods (Irie et al. 2024). This approach is particularly useful in complex decision-making contexts, such as digital health, where multiple competing priorities (e.g. interoperability, digital literacy, data analytics) must be evaluated.
The results of this study indicated that the initiatives "Protect Health Information and Infrastructure Against Cyber-Attacks and Natural Disasters" and "Ensure Information About Healthcare Providers and Services is Current and Accessible" were ranked as the most important. Conversely, the initiatives "Prepare for New Technologies Like AI and Genomics in Healthcare" and "Participate in Evaluations and Provide Feedback on Digital Health Experiences" were ranked as the least important. However, these rankings may partly reflect a preference for initiatives that are perceived as more immediately reassuring or "safe," rather than those that are strategically critical for longer-term digital health transformation. This suggests that stated importance may be influenced by risk aversion and familiarity, potentially undervaluing initiatives that are less tangible but essential for future system capability and innovation.

Most Important Initiatives

The prioritisation of "Protect Health Information and Infrastructure Against Cyber-Attacks and Natural Disasters" and "Ensure Information About Healthcare Providers and Services is Current and Accessible" suggests that respondents value security, reliability, accessibility and trust in digital health.
As digitisation accelerates across healthcare ecosystems, robust cybersecurity becomes increasingly vital to protect computer systems and networks from information breaches, data theft, and malicious damage. The importance of cybersecurity is escalating across all sectors, with healthcare emerging as

a particularly vulnerable and high-stakes domain (Javaid et al. 2023). As healthcare systems increasingly rely on interconnected digital technologies, electronic health records, and complex information networks, they become attractive targets for sophisticated cyber threats that can compromise patient safety, data privacy, and institutional integrity (Jalali and Kaiser 2018; Kruse et al. 2017). Data breaches, identity theft, and ransomware attacks have become prevalent in the healthcare sector due to the volume and type of data stored, including contact information, personal data, social security, and banking information.

Protecting infrastructure against natural disasters is crucial to ensure that digital systems remain functional during emergencies. In Australia, natural disasters such as bushfires, floods, cyclones, and droughts are frequent and severe, causing significant damage to infrastructure and disrupting essential services, including healthcare. The annual cost of natural disasters in Australia is projected to more than double from $18 billion to over $39 billion by 2050 (Australian Government, Infrastructure Australia 2025).

Real-world events, such as healthcare cyber-attacks or system failures during natural disasters, may have shaped public concern. Examples of significant cyber-attacks in Australia, notable attacks include the ransomware attack on the e-prescription delivery service MediSecure in 2024 (Healthcare IT News 2024), the attack on the Australian IVF provider Genea in 2025 (*ABC News* 2025), and the attack on Medibank in 2024 (Taylor 2024). The latter attack resulted in the personal details of 9.7 million customers being published on the dark web. These incidents have likely increased public awareness and undermined public trust in the system's ability to protect sensitive personal and medical data. Consequently, there is a growing demand for stronger cybersecurity measures, stricter government regulations, and greater transparency from healthcare providers. In summary, protecting infrastructure against natural disasters and enhancing cybersecurity measures are both critical to ensuring the resilience and functionality of Australia's healthcare systems.

Accessibility of Health Information

The results demonstrate that respondents value access to health information. Patients and caregivers require comprehensive, readily accessible, and accurate information about healthcare providers, available services, and clinical locations to make informed healthcare decisions (Kwame and Petrucka 2021). This includes detailed provider credentials, specialisation expertise, service availability, geographical accessibility, operational hours, patient-reported experiences, and real-time (virtual/telehealth) service capabilities. Effective health information systems that provide transparent, user-friendly, and current healthcare information can improve patient navigation, reduce healthcare access barriers, and enhance overall patient engagement and decision-making processes (Kwame and Petrucka 2021). The results demonstrate that respondents value access to health information. Patients and caregivers require comprehensive, readily accessible, and accurate information about healthcare providers, available services, and clinical locations to make informed healthcare decisions (Kwame and Petrucka 2021). This includes detailed provider credentials, specialisation expertise, service availability, geographical accessibility, operational hours, patient-reported experiences, and real-time (virtual/tele-health) service capabilities. Effective health information systems that provide transparent, user-friendly, and current healthcare information can improve patient navigation, reduce healthcare access barriers, and enhance overall patient engagement and decision-making processes (Kwame and Petrucka 2021).

Poor information access can lead to delays in treatment, misdiagnosis, or lack of awareness of available healthcare options, negatively impacting individual and community health outcomes (Tiwary et al. 2019). Vulnerable populations, such as elderly individuals, non-native language speakers, and economically disadvantaged communities, are particularly susceptible to these challenges (Rural Health Information Hub 2025). Limited health information access undermines patients' ability to recognise early warning signs, understand complex medical conditions, explore alternative treatment methodologies, and effectively communicate with healthcare providers. These challenges increase psychological stress and feelings of medical disempowerment, perpetuating healthcare inequities and reducing community resilience and individual capacity for proactive health management.

While the topic of healthcare provider information access is critically important for policy development, academic research in this area remains surprisingly sparse. Existing studies have not comprehensively examined the broader impact of provider information accessibility. Instead, researchers have focused on more narrowly defined aspects, such as provider quality metrics (Hannawa et al. 2022), clinical performance measures (Gill et al. 2006), and the various channels through which healthcare provider information is disseminated. These targeted studies provide insights into discrete components of the issue but fall short of offering a holistic understanding of how access to quality health information influences patient decision-making and healthcare system performance.

The experience of COVID-19 pandemic likely played a significant role in shaping respondents' prioritisation of initiatives. The COVID-19 pandemic dramatically transformed how societies perceive and engage with health information and health technology, accelerating digital literacy, challenging traditional information hierarchies, and fundamentally reshaping public trust mechanisms (Aaditya and Rahul 2021). The pandemic revealed weaknesses in how information is shared while fostering more sophisticated information consumption patterns. It made people more skilled at evaluating health information, tracking their health digitally, and assessing risks. The experience of COVID-19 pandemic likely played a significant role in shaping respondents' prioritisation of initiatives. The COVID-19 pandemic dramatically transformed how societies perceive and engage with health information and health technology, accelerating digital literacy, challenging traditional information hierarchies, and fundamentally reshaping public trust mechanisms (Aaditya and Rahul 2021). The pandemic revealed weaknesses in how information is shared while fostering more sophisticated information consumption patterns. It made people more skilled at evaluating health information, tracking their health digitally, and assessing risks.

Least Important Initiatives

The results indicate that respondents may prioritise immediate and tangible benefits, such as access to care, data security, and usability of current digital tools, over future-oriented innovations like AI and genomics. Respondents may perceive AI and genomics as long-term investments rather than pressing concerns. Additionally, AI and genomics are highly technical topics, and the general public may not fully understand their potential impact on healthcare (Davenport and Kalakota 2019). Similar to computers and robots, AI is often personified (Alabed et al. 2022). Rather than having an objective understanding of AI, it is perceived through users' past beliefs and experiences. The way AI is presented in society acts as a primer for its usage, influencing how it is experienced. The collective social imagination and understanding of AI are shaped by the media, fostering both hopes and fears about these technologies. These perceptions often portray AI as either malicious and destructive or overly promising and beneficial. However, such representations do not accurately reflect the state-of-the-art developments in AI research. The actual effectiveness of an AI-driven intervention may be influenced by the user's imagination. This is particularly relevant in the context of the AI black box, where systems are too complicated to comprehend, and so people's imagination plays an important role in explaining them (Miller 2019; Pataranutaporn et al. 2023). At the time of the BWS study, public discourse on AI was only beginning to gain momentum; since then, conversations around AI across all aspects of life have rapidly expanded. Against this backdrop, the benefits of AI and genomic advancements may feel indirect or distant compared to more tangible issues such as electronic health records, telehealth, or affordability. Some respondents may distrust emerging technologies like AI in healthcare, fearing bias, privacy concerns, and errors.

The findings from this BWS study can help inform value assessments that better reflect the priorities of patients, providers, and health system leaders. By capturing what stakeholders consider most and least important in digital health initiatives, the results support more transparent, inclusive, and evidence-informed decision-making within national digital health strategies. This ensures that future investments are aligned with the values and needs of end users, while also addressing broader system-level goals.

Limitations

One significant limitation of this study is the total number of items and total number of choice tasks included. The high number of initiatives made the task of consistently identifying the most and least important items within each set more demanding, potentially leading to cognitive fatigue. This fatigue could compromise the quality of responses, as respondents may resort to satisficing (choosing acceptable rather than optimal responses) to complete the survey more quickly and with less mental effort. Additionally, the complexity and technical nature of the initiatives and tasks could result in inconsistent rankings and reduced attention to nuanced differences between items. Treating these initiatives as objects treated as either most important or least important, may have restricted the expression of a gradient in the perceived importance of individual components of the initiatives. This may have impacted the rankings and had an impact on the heterogeneity in the data. Translating descriptive content into valuation-ready statements is inherently complex, and incorporating qualitative methods could strengthen the rigour of future work. To improve the validity and interpretability of such statements, future research may benefit from formal iterative approaches, including cognitive testing and expert reconciliation processes. Participating in evaluations and providing feedback on digital health experiences, such as through BWS surveys, requires significant effort from respondents. Survey fatigue is a major issue, as individuals are frequently inundated with survey requests, leading to a diminished motivation to respond (Ghafourifard 2024). Additionally, respondents may perceive the survey topics as irrelevant to their personal experiences, reducing their engagement. Finally, insufficient incentives can make respondents less willing to invest their time and effort (Grewenig et al. 2022). Addressing these barriers is crucial to improving participation rates and the quality of feedback in digital health evaluations.

In our analysis substantial heterogeneity in preferences across different NDHS initiatives was observed, which may be perceived as most important by different subgroups. The subgroup analysis was exploratory in nature and lacked statistical power given the number of respondents in the sub-groups, as the experiment was not specifically designed for subgroup comparisons. Due to the constraints of the BIBD structure, the number of times each item appeared across subgroups was limited, reducing the precision and reliability of subgroup-specific estimates.

These limitations highlight the need for further research and the adoption of alternative approaches, such as refined survey designs based on this study's findings or complementary approaches that minimise cognitive load and response bias. Future survey designs could focus on a reduced set of the most important items (NDHS initiatives) while accounting for changes and progress in NDHS initiatives that have occurred between this study's development and their current implementation status. In addition, alternative stated-preference methods such as discrete choice experiments (DCEs) may provide complementary insights by incorporating information on trade-offs and opportunity costs, which might influence how individuals prioritise initiatives. Exploring such approaches could help capture a broader range of considerations in future evaluations

Chapter 8: Discussion

This thesis explores the perceived value and benefits associated with digital health technologies (DHTs) by investigating public preferences for investment priorities related to DHTs. Specifically, the thesis examines how the value of digital health technologies (DHTs) can be understood by bringing together three domains: digital maturity, economic value, and user preferences. Rather than treating these as separate and parallel concepts, concepts. The central argument of this thesis is that value in digital health emerges at the intersection of these concepts. Digital maturity shapes what can be implemented and sustained; economic evaluation determines what is deemed efficient or worthwhile use of resources, and user preferences influence whether technologies are accepted, trusted, and effective in practice, and how they are ultimately valued. A key contribution of this work is therefore to demonstrate how these domains interact across different levels of the health system, and why evaluating DHTs requires an integrated, rather than siloed, perspective, that takes into account all these aspects.

The first chapters established that the existing frameworks for assessing digital health maturity to understand how these align with stakeholder expectations and system-level goals. While the promise of DHTs lies in their ability to transform healthcare delivery, their successful integration depends on a rigorous and context-sensitive understanding of value, one that goes beyond narrow measures of cost-efficiency to include acceptability, usability, and the ways in which technologies reshape care. Drawing on insights from the scoping review and consultation with clinicians and experts in stated preference (SP) research, three empirical studies were conducted using SP methods, specifically two discrete choice experiments (DCEs) and one best-worst scaling (BWS) study. The BWS of the Australian National Digital Strategy represents a top-down, system-level perspective, focusing on the system-wide approach to and framework for establishment of digital health infrastructure and its implications for health outcomes and the healthcare ecosystem. The two DCE studies, which consider the use of AI in oncology case provide the opportunity to focus on how digital innovations influence care delivery in a specific clinical setting and how these changes shape stakeholder attitudes and acceptance, and perceptions of value.

The scoping review (Chapter 3) illustrated both the potential and the limitations of current evaluation practices. Economic studies of AI in oncology often conclude that interventions are cost-effective, yet these assessments typically rely on assumptions about accuracy and costs, rather than clinical effectiveness data or real-world implementation, including acceptability to consumers and providers. This highlights a critical need for more primary effectiveness research specific to AI applications in cancer care to strengthen future economic evaluations.

Conventional models often treat technologies as static, when in fact digital tools, particularly AI, are dynamic learning systems that evolve as data accumulate. The review's findings highlight that digital technologies cannot be fully understood in isolation from their context. Their value depends not only on algorithmic performance but also on how they integrate into workflows, interact with health professionals, and meet the expectations of patients.

The importance of broader context for adoption of digital technologies motivated the decision to adopt a case study approach in the empirical chapters, which allowed examination of digital health within both a specific clinical setting and in the framework of broader system-wide strategy. The important link between these two cases, respectively at the macro and micro level of the health system, is the central importance of understanding how stakeholders across the health system perceive and evaluate the value of digital health innovations. This thesis advances knowledge by showing that economic value cannot be robustly assessed without understanding how technologies interact with clinical workflows, governance structures, and user expectations. In doing so, it reframes economic evaluation as a necessary but insufficient component of digital health assessment.

The use of AI in radiation therapy case studies (Chapters 5 and 6) provided a detailed examination of consumers preferences for adopting these technologies in clinical practice. Both professionals and the general public valued accuracy and timeliness. Clinicians preferred assistive systems that enhanced rather than replaced their expertise, and patients wanted reassurance that human oversight would remain central to their care. These findings indicate that value extends beyond clinical outcomes to encompass dimensions such as trust, transparency, and the preservation of human judgment in high-stakes care. Importantly, the studies also highlighted that efficiency gains should not be assumed as AI technologies may shift workloads rather than reduce them, and adoption depends on seamless integration into existing systems. This points to a multidimensional understanding of value, which recognises clinical, organisational, ethical, and experiential dimensions.

The findings from the DCEs offer valuable inputs for future economic evaluations. The relative importance weights derived from the DCEs quantify how individuals value different aspects of DHTs, many of which may fall outside the scope of traditional health outcome measures used in economic evaluation (such as QALYs or more narrow outcomes such as cases detected). As such, the DCE research presented in this thesis helps to identify outcomes and features that matter to consumers and providers but are often overlooked in conventional economic evaluations. The results provide insight about the preferences of stakeholders (consumers and providers) for attributes such as data governance, interoperability, trust, and system readiness. These are dimensions that may be absent in standard CEA/CUA frameworks, which are primarily oriented towards health outcomes and short-term efficiency gains. While alternative approaches such as MCDA, capability-based frameworks (e.g. ICECAP), and Social Return on Investment have been proposed to broaden the evaluative lens, their limited uptake reflects ongoing challenges around methodological complexity, data requirements, and lack of institutional guidance.

In the context of digital health, the findings suggest that more holistic approaches, such as MCDA and similar frameworks are particularly well suited, as they provide a transparent structure for incorporating non-health and system-level criteria without displacing established economic evidence. The stated preference results presented in this thesis make a distinct contribution by empirically quantifying the relative importance of these criteria, offering a basis for weighting within such frameworks rather than relying on expert judgement alone. In practical terms, these insights can be integrated by embedding preference-derived weights into MCDA-informed HTA processes, or by using them to complement CEA/CUA results in deliberative decision-making. The insights from stated preference research can be used to supplement or adapt existing evaluation frameworks, ensuring they more accurately capture the broader and multi-dimensional value of digital health interventions.

In contrast to the DCEs, the evaluation of the Australian National Digital Health Strategy (Chapter 7) undertaken using a BWS approach, provided a broader, system-level perspective, shifting the focus from specific innovations to the foundations of digital health infrastructure and governance. The results of this study showed the public's priorities were focused on data security, reliability of health information, and resilience of digital infrastructure as issues that feel immediate, and tangible compared with more future-oriented innovations such as AI and genomics. This may indicate risk perceptions shaped by cybersecurity breach incidents and natural disasters as well as a desire for digital health systems to address foundational needs before advancing into more complex domains. These results demonstrate that public expectations are often grounded in day-to-day realities, and that investment decisions must balance long-term innovation with present demands for safety, accessibility, and equity. When synthesised with the findings form the DCEs, this suggests that digital maturity is not simply about advancing technological sophistication, but about establishing trust-enabling foundations that legitimise further innovation. This bridges the gap between system-level strategy and individual-level acceptance, reinforcing the thesis's overarching argument that maturity, value, and preference are mutually reinforcing.

The results from the DCE and BWS studies capture what stakeholders perceive as valuable based on their current experiences, knowledge, and expectations, making them highly relevant for assessing acceptability, legitimacy, and alignment with immediate system priorities. However, these preferences may undervalue attributes with long-term, system-level, or option value, particularly where benefits are uncertain, diffuse, or not yet visible to end users. This is illustrated by the lower priority assigned to the initiatives such as "preparing for new technologies like AI" presented in Chapter 7, as well as by the apparent tension in preferences for both maintaining human oversight and achieving efficiency gains through automation. While stakeholders value the reassurance, accountability, and trust associated with keeping a human in the loop, this preference inherently constrains the time-saving and efficiency benefits that AI-enabled technologies promise. Such findings highlight that stated preferences may be internally inconsistent or reflect trade-offs that are not fully recognised by respondents. Such tensions between the stated preferences may provide important signals for policymakers about the boundaries of acceptable implementation. In this context, economic evaluation frameworks should use stated preference evidence to inform structured trade-offs, weighing efficiency gains against requirements for oversight, safety, and trust. Accordingly, the empirical findings in this thesis should be interpreted as informing, rather than determining, resource allocation decisions, by clarifying where efficiency-driven innovations may require complementary governance or staged implementation to align with societal values.

Evaluating digital health technologies requires rethinking the concept of "value." By combining economic evidence with stakeholder insights and considering technologies within their real-world contexts, this thesis presents a multidimensional framework for understanding the value of DHTs. This approach not only assists policymakers in prioritising investments but also ensures that the adoption of digital innovations reflects the needs and values of patients, providers, and the wider health system.

In synthesis, this thesis moves beyond asking whether digital health technologies are cost-effective or technologically mature and instead addresses whether they are valued in ways that support sustainable, equitable, and trusted healthcare delivery . This thesis has shown that the value of DHTs emerges at the intersection of technical capability, system readiness, and societal expectation. By studying stakeholder perspectives in addition to economic and maturity assessment frameworks, this thesis contributes to a more holistic and pragmatic approach to evaluation of digital health technologies.

The work presented in this thesis highlights a that digital maturity is not a destination but a continuous process of alignment between innovation, evidence, and the values of the communities these technologies are designed to serve. Rather than requiring entirely new evaluation frameworks, the findings in this thesis support a set of guiding principles for digital health HTA. This can be done by embedding preference-derived importance weights within MCDA-based appraisal structures, enabling systematic incorporation of non-health and system-level criteria, such as trust, data governance, interoperability, and workforce impacts, alongside conventional clinical and economic evidence. A complementary pathway is to use stated preference results to inform deliberative HTA and reimbursement processes by contextualising CEA/CUA outputs, particularly where technologies generate benefits or risks that are poorly captured by QALYs alone. Finally, the preference patterns identified in this thesis can inform staged implementation strategies and governance design, highlighting where efficiency-driven deployment may require safeguards, human oversight, or infrastructure investment to align with stakeholder expectations.

Taken together, these applications support a set of guiding principles for HTA of digital health technologies, explicit recognition of multi-dimensional value, structured incorporation of stakeholder preferences into appraisal processes, and alignment of short-term efficiency objectives with longer-term system capability, legitimacy, and resilience.

Limitations and challenges

The research presented in this thesis, while making significant contributions to understanding the value of digital health maturity, faced several important limitations that should be acknowledged.

Methodological Limitations

The SP research methodologies employed in this thesis, particularly the DCEs and BWS, carry inherent limitations. These approaches rely on hypothetical scenarios rather than observed behaviours, which may not perfectly reflect real-world decision-making processes. Respondents' SPs might differ from their actual choices when faced with similar situations in real life although most people do as they say in those studies that have been able to compare the two (Salampessy et al. 2022; Quaife et al. 2018).
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The exploratory nature of the BWS study, while providing valuable initial insights, requires follow-up research to validate and expand upon its findings. The BWS methodology offered a useful approach for prioritising digital health initiatives, but the results should be interpreted with caution until further validation studies are conducted.

A significant limitation was the rapidly evolving nature of DHTs, particularly AI applications. The fast pace of technological advancement in this field meant the currency and relevance of some of the findings may be time limited as technologies evolve.

The research was conducted during a period of substantial change in digital health policy and practice in Australia. This dynamic environment created challenges in establishing stable parameters for the evaluation framework. There are ongoing developments in Australia's National Digital Health Strategy (2023-2028), which is designed as a "living document" subject to continuous revision and adaptation. The evolving nature of this strategic framework presents challenges in establishing fixed reference points for evaluating digital health initiatives. The single-country (Australia) and radiation oncology focus may limit the generalisability of these findings to other settings.

Practical Research Challenges

The case study approach adopted for evaluating the digital maturity ecosystem, while necessary given the complexity of the field, may limit the generalisability of some findings. Different healthcare settings may present unique challenges and opportunities not captured in the selected case studies.

One of the key limitations of this thesis was the challenge of identifying and developing relevant case studies that were directly drawn from the implementation of digital health infrastructure for Sydney Local Health District, the DHCRC industry partner for this research. This challenge was significantly compounded by the impact of the COVID-19 pandemic, which not only disrupted healthcare operations but also delayed the rollout of digital health infrastructure across the Sydney Local Health District (SHLD). As a result, the timeline for deploying the digital health systems was extended well beyond initial projections, making it difficult to source timely case studies (where the rollout was at the appropriate stage for evaluation) directly from the SHLD implementation that could provide meaningful insights into the costs and impacts of digital health within the local health district. Consequently, the research pivoted to focus on identifying and analysing relevant case studies from comparable and relevant contexts, allowing for a broader understanding of digital health implementation that could be applied to the SHLD context.

Future Research Directions

There are several promising research directions that have emerged from the findings of this thesis that could address identified limitations and further advance knowledge in this field. These research directions were beyond the scope of the thesis, but future research could build upon this work through three key directions.

First, a valuable next step would be a targeted evaluation of AI technologies. This could involve conducting a follow-up discrete choice experiment (DCE) focused on AI tools that are already in use in clinical practice, in contrast to the current study's emphasis on earlier-stage technologies. Such a study could be complemented by a modelled economic evaluation, using DCE findings to assess the cost-effectiveness of particular AI systems in radiation oncology. With a focus on the Australian healthcare context, these models would help fill critical evidence gaps and provide insights to guide practical implementation decisions.

Another important direction would be to explore the role of patient-reported outcomes measures (PROMs) in the evaluation of AI technologies in oncology. This includes examining how non-preference-based PROMs can be mapped to utility values. Doing so would strengthen the capacity to conduct robust economic evaluations that reflect the distinctive features of AI technologies within the Australian context. DCEs could also be applied to value the domains of these PROMs, enabling their conversion into preference-based, utility-compatible measures. This approach would mirror the development of widely used instruments, such as the EQ-5D, and extend their applicability to AI-focused evaluations.

Finally, while the BWS presented in this thesis provides insights for policy makers into what is most important for consumers and the general population in developing a framework to support digital health rollout across the health system, it was evident that the level of detail and the complexity of the priorities in the overall framework are challenging for respondents. Based on the findings of this initial BWS there is an opportunity to develop a more focussed list of initiatives to allow for clearer guidance for policy makers and health care leaders. The findings from the work presented in this thesis could be the basis, combined with guidance from previous methodological work for a more focussed preference study in which it would be possible to refine the design of the task in terms of number of items considered in the exercise, number of BWS tasks in the questionnaire, and the number of respondents.

These future research directions will build upon the foundation established in this thesis, addressing identified limitations while furthering our understanding of how to evaluate and optimise digital health investments.

Overall conclusion

This thesis provides a structured and detailed exploration of how the value of DHTs can be understood, measured, and applied to inform policy and investment decisions, providing insights both at the level of health systems and for particular technologies. Through a combination of empirical research, and literature review, it sheds light on the preferences and priorities of key stakeholders, including healthcare professionals, patients, and the general public, when assessing DHTs such as AI in radiation therapy and system-wide digital health initiatives included in the Australian National Digital Health Strategy.

The findings highlight the need for robust, multidimensional frameworks to evaluate the evolving landscape of DHTs. Traditional economic evaluation methods may not fully capture the complexity and dynamic nature of these technologies. Incorporating stakeholder preferences through SP methods provides valuable insights into dimensions of value, such as data privacy, explainability, integration, and timeliness, that are often underrepresented in conventional health technology assessments.

The studies presented here offer actionable evidence to inform the design and implementation of DHTs that are not only clinically and economically sound but also aligned with end-user values. Moreover, the results can feed into more nuanced economic evaluations and digital maturity assessments that better reflect real-world needs and constraints.

Taken together, the thesis contributes to a growing body of evidence supporting the use of preference-based approaches in digital health evaluation. It demonstrates how these methods can enhance the relevance and responsiveness of investment decisions in publicly funded healthcare systems. As digital health technologies continue to evolve and reshape healthcare delivery, stakeholder-centred frameworks will be critical to guide responsible, scalable, and value-based adoption across the health system.

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Appendices

Appendix 1

Table A1.1: Overview of the key international guidance relevant to digital health and AI

Document Title	Organisation Responsible	Description/Aims	Areas of Interest
WHO Global Strategy on Digital Health 2020-2025 (WHO 2021)	World Health Organization (WHO)	The strategy aims to enhance health systems globally by integrating digital health solutions. It focuses on improving health outcomes, ensuring equitable access to health services, and encouraging countries to develop robust digital health strategies aligned with global standards.	Global digital health strategies, health promotion
General Data Protection Regulation (GDPR)(European Commission 2018)	European Commission	Sets a comprehensive data protection law enacted by the European Union (EU) to safeguard personal data and privacy for individuals within the EU.	Data protection, privacy, personal health data
Medical Device Regulation (MDR); Regulation (EU) 2017/745 (EUR-Lex 2017)	European Commission	A comprehensive regulatory framework established by the European Union to ensure the safety and performance of medical devices, including software as a medical device (SaMD).	Medical devices and their accessories, safety, SaMD
EU Artificial Intelligence Act (AI Act) 2024 (European Commission 2024)	European Commission	Regulatory framework aimed at ensuring the safe and ethical development and deployment of AI technologies across the EU. Regulates AI systems based on risk, ensuring safety and fundamental rights protection.	AI systems, risk management, innovation, fundamental rights
European Health Data Space (EHDS) 2025 (European Commission 2025b)	European Commission	Establishes a framework for the use and exchange of electronic health data	Health data exchange, data reuse, digital health services
Medical Devices Regulations 2002 (SaMD); AIaMD 2022 (UK Government, Department of Health & Scocial Services 2025)	UK, Medicines and Healthcare products Regulatory Agency (MHRA)	Covers regulatory frameworks, digital health technologies, data use, SaMD and AIaMD	Regulatory frameworks, data use, AI, liability
UK General Data Protection Regulation (UK GDPR) and Data Protection Act 2018 (UK Government 2018)		The GDPR is UK law that governs the processing of personal data within the UK and ensures that individuals' data rights are protected. The Data Protection Act 2018 complements the UK GDPR and provides a comprehensive framework for data protection in the UK.	Data protection, privacy, personal health data
FDA Guidance Documents for Digital Health: 510(k) certification 2017; Premarket Approval (PMA) 2022; SaMD 2017; Digital Health Software Pre-	U.S. Food and Drug Administration (FDA)	Provides clarity on the FDA's regulation of digital health products;	Medical devices, SaMD, AI, cybersecurity, clinical decision support, Computer-Assisted Detection Devices Applied to Radiology Images and Radiology Device Data , laboratory tests

Document Title	Organisation Responsible	Description/Aims	Areas of Interest
certification Program 2017; and Laboratory Developed Test (C. for D. and R. H. FDA 2025)			
Health Insurance Portability and Accountability Act (HIPPA) 1996 (CDC 2024)	US Federal law	Provides protection of sensitive patient health information from being disclosed without the patient's consent or knowledge. Applies to any provider who transmits health information in electronic form in connection with certain transactions.	Data privacy rules
Regulations on Supervision and Administration of Medical Devices (2022) (China NMPA 2022)	National Medical Products Administration (NMPA), China	Regulates digital health apps and mobile medical devices.	Medical devices, mobile health, safety and efficacy
Digital Information Security in Healthcare Act (DISHA) 2018 The Digital Personal Data Protection Act (DPDP Act) 2023 (Jain 2023)	Ministry of Health and Family Welfare, the National Digital Health Authority (NeHA), India	Defines digital health data and sets standards for data security and privacy	Data security, privacy, health information

Table A1.2: Overview of the key Australian regulations relevant to digital health and AI

Document Title	Organisation Responsible	Short Description	Areas of Interest
Therapeutic Goods Act 1989 (Australian Government 2025b)	Therapeutic Goods Administration (TGA)	This TG Act establishes a national system for regulating the quality, safety, efficacy, and timely availability of therapeutic goods in Australia	Import, export, manufacture, and supply of therapeutic goods; listing and registering medicines, medical devices, and biological products; advertising and labelling requirements
The My Health Record Act 2012 (Australian Government 2025a)	Therapeutic Goods Administration (TGA)	The Act governs the My Health Record system, which allows individuals to have an online summary of their key health information	Privacy and security of health information; roles and responsibilities of the System Operator; registration framework for individuals and healthcare providers
The Healthcare Identifiers Act 2010 (Australian Government 2024)	Therapeutic Goods Administration (TGA)	This act provides a system for assigning unique healthcare identifiers to individuals and healthcare providers to ensure accurate matching of health information	Assigning and managing healthcare identifiers; privacy and security of identifying information; integration with the My Health Record system
Therapeutic Goods Administration (TGA) Medical Device Regulation, SaMD (TGA 2021)	Therapeutic Goods Administration (TGA)	Regulates digital health technologies as medical devices, including SaMD and digital therapeutics	Medical devices, safety, efficacy
Australian Digital Health Agency (ADHA) Standards (ADHA 2025b)	Australian Digital Health Agency (ADHA)	Develops standards to enable connected care and supports the implementation of the Australian National Digital Health Strategy	Connected care, digital health standards

Table A1.3: AI risk classification, EU AI Act

Risk classification	Description
Minimal risk	These AI systems pose minimal or no risk to individuals' rights or safety and are largely unregulated under the EU AI Act (e.g. AI-enabled video games).
Limited risk (specific transparency risk)	AI systems (e.g. ChatGPT) that need to comply with specific transparency compliance and EU copyright law. This includes disclosing that the content was generated with AI, publishing summaries of copyrighted data used for training and designing the model that prevents it from generating illegal content
High risk:	AI systems that negatively affect safety or fundamental rights will be considered high risk and will be divided into two categories: AI systems that are included in the products protected by the EU's product safety legislation (e.g. medical devices, cars, toys) and AI systems that fall into specific area that requires to be registered in an EU database (e.g. education, law enforcement). All high-risk AI systems need to be assessed before being out on the market and throughout their product life-cycle
Unacceptable risk (prohibited AI systems)	AI systems that pose threat to humanity and will be banned (i.e. cognitive behavioural manipulation of people of specific vulnerable groups, biometric categorisation of people). It is noted that some exceptions may be allowed, such as for law enforcement purposes

Source: (European Parliament Panel for Future of Science and Technology 2023; European Commission 2025a)

Appendix 2

Nil

Appendix 3

Table A3.1: Scoping review: search terms

Database	Search terms	Filters
PubMed	(("Artificial Intelligence"[Mesh]OR "Artificial Intelligence"[tiab] OR "Machine Learning"[Mesh] OR "Machine Learning"[tiab] OR "Deep Learning"[tiab]) AND ("Oncology"[tiab] OR "Cancer"[tiab] OR "Neoplasms"[Mesh] OR "Neoplasms"[tiab]) AND ("Economics"[Mesh] OR "Economic Evaluation"[tiab] OR "Cost-Benefit Analysis"[Mesh] OR "Cost-Benefit Analysis"[tiab] OR "Cost-Effectiveness"[tiab] OR "Budget Impact"[tiab]))	Years: 2019-April 2025 Language: English
Scopus	(TITLE-ABS-KEY ("artificial intelligence" OR "machine learning" OR "deep learning")) AND (TITLE-ABS-KEY ("oncology" OR "cancer" OR "neoplasms")) AND (TITLE-ABS-KEY ("economics" OR "economic evaluation" OR "cost-benefit analysis" OR "cost-effectiveness" OR "budget impact")) AND PUBYEAR > 2018 AND PUBYEAR < 2026 AND (LIMIT-TO (DOCTYPE , "re") OR LIMIT-TO (DOCTYPE , "ar") OR LIMIT-TO (DOCTYPE , "cp"))	Years: 2019-April 2025 Language: English
Google Scholar	"artificial intelligence" "machine learning" "deep learning" automation "economic evaluation" OR "cost-effectiveness" OR "cost-benefit" OR "cost-utility" "radiation therapy" "treatment planning"	Years: 2019-April 2025

Table A3.2: CHEERS-AU checklist

	Ahsen 2025	Borsoi 2024	Hill 2024	Mital 2022	Vargas 2023	Shen 2023	Adams 2021	Barkun 2023	Bustamante-Balén, 2025	Kacew, 2021	Mori, 2020	Ar-iea, 2022	Li-banio, 2024	Yonazu, 2023	Geng, 2025	Huang, 2025	Ziegelmayer, 2022	Tru-jillo, 2025	Gomez Rossi, 2022	Du, 2024	Marka, 202
Author/Year/Abstract	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Title	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Population	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Comparator	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Time horizon/cycle length	0	1	1	1	0	1	1	1	1	1	0	1	0..5	1	0	0	1	1	1	1	1
Perspective	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Discount rate	0	0	1	1	0	1	0	1	1	0	0	1	1	1	0	0	1	1	1	1	1
Background/ Objectives	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
HE analsysis plan	0	1	1	1	1	1	0	1	1	1	0	1	1	1	0	0	1	1	1	0	1
Setting and location	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0.5
Selection of outcomes	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Measurements of outcomes	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Valuatioin of outcomes	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Measureemnt and valuation of resources and costs	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Currency, price date and conver-sion	0.5	0	1	1	1	1	0	0	1	0	0	0	0	1	0	0	0	0	1	1	0
Rationale and description of the model	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1
Analysis and assumptions	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	0	1	1	1	1
Characterising heterogeneity	1	1	0	1	0	0	1	0	0	0	0	1	1	0	0	0	0	0	0	1	0
Characterisling distributional ef-fects	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0

	Ahsen 2025	Borsoi 2024	Hill 2024	Mital 2022	Vargas 2023	Shen 2023	Adams 2021	Barkun 2023	Bustamante-Balén, 2025	Kacew, 2021	Mori, 2020	Ar-iea, 2022	Libanio, 2024	Yonazu, 2023	Geng, 2025	Huang, 2025	Ziegelmayer, 2022	Trujillo, 2025	Gomez Rossi, 2022	Du, 2024	Marka, 202
Characterising uncertainty	0	1	1	1	1	1	0	1	1	0	0	1	1	1	0	0	1	1	1	0	1
Approach to engaging with patients and others affected by the study	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Study parameters	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Summary of main results	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Effect of uncertainty	0	0	1	1	1	1	0	1	1	0	0	1	1	1	0	0	1	1	1	0	1
Effect of engagement with opatients and other affected by the study	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Study findings, limitations, generalisability, and current knowledge	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Source of funding	0	1	1	1	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1
Conflict of interest	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1
User autonomy	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Measurements of AI effect	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Measurement of AI learning over time	0	1	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	1
Development of AI component	0	1	0	0	0	0	1	0	0	1	1	0	0	0	1	1	0	0	0	0	1
Validation of AI component	0	0	0	1	0	0	1	1	0	1	0	0	0	0	0	1	0	0	0	0	1
Health Benefit	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	1	0	1	1	0	1
Population differences	0.5	0	0	0	0	0	1	1	0	0	1	0	0	0	0	0	0	0	0	0	1
Modelling of AI learning over time	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Impact of AI uncertainty	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Implementation of AI	1	1	0	0	1	0	0	1	1	0	1	0	0	0	0	1	0	0	0	1	0

	Ahsen 2025	Borsoi 2024	Hill 2024	Mital 2022	Vargas 2023	Shen 2023	Adams 2021	Barkun 2023	Bustamante-Balén, 2025	Kacew, 2021	Mori, 2020	Ariea, 2022	Libanio, 2024	Yonazu, 2023	Geng, 2025	Huang, 2025	Ziegelmayer, 2022	Trujillo, 2025	Gomez Rossi, 2022	Du, 2024	Marka, 202
Score (indiv. Studies)	61%	76%	68%	76%	66%	71%	74%	76%	74%	66%	61%	68%	68%	71%	50%	58%	63%	68%	71%	66%	78%

Table A3.3: Philips checklist

	Ahsen 2025	Borsoi, 2024	Hill, 2024	Mital, 2022	Vargas, 2023	Shen, 2023	Adams, 2021	Barkun, 2023	Bustamante-Balén, 2025	Kacew, 2021	Mori, 2020	Ariea, 2022	Libanio, 2024	Yonazu, 2023	Geng, 2025	Huang, 2025	Ziegelmayer, 2022	Trujillo, 2025	Gomez Rossi, 2022	Du, 2024	Marka, 202
Statement of decision problem/objective	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Statement of scope/perspective	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Rationale for structure	N	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
structural assumptions	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	N	N	Y	Y	Y	Y
Strategies/comparators	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Model type	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Time horizon	N	Y	Y	Y	N	Y	Y	Y	Y	Y	N	Y	Y	Y	N	N	Y	Y	Y	Y	Y
Disease states/pathways	N	Y	Y	Y	Y	Y	N	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Cycle length	N	N	N	Y	N	N	N	Y	Y	N	N	Y	Y	N	N	N	N	Y	Y	N	N
Data identification	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Data modelling	N	Y	Y	Y	Y	Y	N	Y	Y	Y	N	Y	Y	Y	Y	N	Y	Y	Y	N	Y
Baseline data	N	Y	N	N	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	N	N	Y

	Ah-sen 2025	Bor-soi, 2024	Hill, 2024	Mital, 2022	Var-gas, 2023	Shen, 2023	Ad-ams, 2021	Barkun, 2023	Bustamante-Balén, 2025	Kacew, 2021	Mori, 2020	Ar-iea, 2022	Li-banio, 2024	Yonazu, 2023	Geng, 2025	Huang, 2025	Ziegelmayer, 2022	Tru-jillo, 2025	Gomez Rossi, 2022	Du, 2024	Marka, 202
Treatment effects	N	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	Y	Y
Costs	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Quality of life weights (utilities)	N	Y	Y	Y	Y	Y	N	Y	Y	N	N	N	Y	Y	N	N	Y	Y	Y	N	Y
Data incorporation	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Assessment of uncertainty	N	Y	Y	Y	Y	Y	N	Y	Y	N	N	Y	Y	Y	N	N	Y	Y	Y	N	Y
Methodological	N/A	Y	N	N	N	N	N	N	Y	N/A	N/A	Y	N	N	N/A	N/A	N	N	Y	N/A	Y
Structiral	N/A	Y	N	N	N	Y	N	N	Y	N/A	N/A	N	N	N	N/A	N/A	N	N	Y	N/A	Y
Heterogeneity	N/A	Y	N	N	N	N	N	N	N	N/A	N/A	N	N	N	N/A	N/A	N	N	N	N/A	N
Parameter	N/A	Y	Y	Y	Y	Y	N	Y	Y	N/A	N/A	Y	Y	Y	N/A	N/A	Y	Y	Y	N/A	Y
Internal consistency		NA	Y	Y	Y	Y	Y	Y	Y	Y	N	Y	Y	Y	Y	N	Y	Y	Y	N	Y
External consistency		NA	Y	Y	N	Y	N	Y	Y	Y	N	Y	Y	Y	Y	N	N	Y	N	N	N

Appendix 4

Nil

Appendix 5

Figure A5.1: Preferences among healthcare professionals (Ethics approval)

Centre for Health Economics Research and Evaluation (CHERE)

10 November 2023

Dear Milena

RE: Preferences for adopting artificial intelligence in radiation therapy treatment: A discrete choice experiment

Thank you for providing additional information about this research and submitting a revised request. The CHERE management team has agreed that this research is appropriate to be conducted under CHERE's program ethics approval from the UTS Human Research Ethics Committee (UTS HREC REF NO. ETH21-6090).

Yours sincerely

Production Note:
Signature removed prior to publication.

Jane Hall
Distinguished Professor, CHERE

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Figure A5.2: A checklist for conjoint analysis application in health care.

Table 1 – A checklist for conjoint analysis applications in health care.

1. Was a well-defined research question stated and is conjoint analysis an appropriate method for answering it?
   - 1.1 Were a well-defined research question and a testable hypothesis articulated?
   - 1.2 Was the study perspective described, and was the study placed in a particular decision-making or policy context?
   - 1.3 What is the rationale for using conjoint analysis to answer the research question?
2. Was the choice of attributes and levels supported by evidence?
   - 2.1 Was attribute identification supported by evidence (literature reviews, focus groups, or other scientific methods)?
   - 2.2 Was attribute selection justified and consistent with theory?
   - 2.3 Was level selection for each attribute justified by the evidence and consistent with the study perspective and hypothesis?
3. Was the construction of tasks appropriate?
   - 3.1 Was the number of attributes in each conjoint task justified (that is, full or partial profile)?
   - 3.2 Was the number of profiles in each conjoint task justified?
   - 3.3 Was (should) an opt-out or a status-quo alternative (be) included?
4. Was the choice of experimental design justified and evaluated?
   - 4.1 Was the choice of experimental design justified? Were alternative experimental designs considered?
   - 4.2 Were the properties of the experimental design evaluated?
   - 4.3 Was the number of conjoint tasks included in the data-collection instrument appropriate?
5. Were preferences elicited appropriately, given the research question?
   - 5.1 Was there sufficient motivation and explanation of conjoint tasks?
   - 5.2 Was an appropriate elicitation format (that is, rating, ranking, or choice) used? Did (should) the elicitation format allow for indifference?
   - 5.3 In addition to preference elicitation, did the conjoint tasks include other qualifying questions (for example, strength of preference, confidence in response, and other methods)?
6. Was the data collection instrument designed appropriately?
   - 6.1 Was appropriate respondent information collected (such as sociodemographic, attitudinal, health history or status, and treatment experience)?
   - 6.2 Were the attributes and levels defined, and was any contextual information provided?
   - 6.3 Was the level of burden of the data-collection instrument appropriate? Were respondents encouraged and motivated?
7. Was the data-collection plan appropriate?
   - 7.1 Was the sampling strategy justified (for example, sample size, stratification, and recruitment)?
   - 7.2 Was the mode of administration justified and appropriate (for example, face-to-face, pen-and-paper, web-based)?
   - 7.3 Were ethical considerations addressed (for example, recruitment, information and/or consent, compensation)?
8. Were statistical analyses and model estimations appropriate?
   - 8.1 Were respondent characteristics examined and tested?
   - 8.2 Was the quality of the responses examined (for example, rationality, validity, reliability)?
   - 8.3 Was model estimation conducted appropriately? Were issues of clustering and subgroups handled appropriately?
9. Were the results and conclusions valid?
   - 9.1 Did study results reflect testable hypotheses and account for statistical uncertainty?
   - 9.2 Were study conclusions supported by the evidence and compared with existing findings in the literature?
   - 9.3 Were study limitations and generalizability adequately discussed?
10. Was the study presentation clear, concise, and complete?
    - 10.1 Was study importance and research context adequately motivated?
    - 10.2 Were the study data-collection instrument and methods described?
    - 10.3 Were the study implications clearly stated and understandable to a wide audience?

Source: Table 1 p 406, Bridges et al 2011 (Bridges et al. 2011)

Figure A5.3: DCE 1: Preferences among healthcare professionals (survey screenshots)

UTS HREC REF NO. ETH21-6090 - Use of artificial intelligence (AI) in radiation therapy

What is the research about?
The purpose of this research is to explore health care professionals (HCPs) preferences and attitudes about the adoption of AI in the radiation therapy planning and preparation process.
Your responses will be used to help inform decision makers in Australia about what is important to HCPs when thinking about the current and potential future applications of AI in radiation therapy treatment planning. The survey is for HCPs who are involved in the radiation therapy treatment planning process.
The survey is expected to take about 15 minutes to complete. We will ask you to consider some hypothetical scenarios and choose your preferred option, and then ask you some questions about yourself and your opinions.

Who is conducting this research?
This study is undertaken by Milena Lewandowska, Prof Rosalie Viney, and Prof Deborah Street at the Centre for Health Economics Research and Evaluation at the University of Technology Sydney. The research is a part of a PhD (Milena Lewandowska) funded by the Digital Health Collaborative Research Centre (DHCRC). The study has been approved by the University of Technology Sydney UTS HREC REF NO. ETH21-6090

Do I have to take part in this research study?
Participation in this study is voluntary. It is completely up to you whether or not you take part. If you decide to take part, please continue with the survey by completing the questions below and clicking on NEXT. If you begin, you can change your mind at any time and stop completing the survey.

Are there any risks/inconvenience?
We don't expect that participation in this questionnaire will cause any harm or discomfort.

What will happen to the information collected?
The survey is anonymous, and your identity can never be linked to your answers. Submission of this online questionnaire is an indication of your consent to the research team collecting and using your answers to the questions for the research project. At the end of this research, we will store the survey data, and it may also be used in other related research. The data will always be treated confidentially. We plan to publish the results of this research in academic journals and reports for medical organisations and health departments.

What if I have concerns or a complaint?
If you have concerns about the research that you think we can help you with, please feel free to contact Rosalie Viney at Rosalie.Viney@uts.edu.au or Milena Lewandowska at Milena.Lewandowska@uts.edu.au. If you would like to talk to someone who is not connected with the research, you may contact the Research Ethics Officer on 02 9514 1793 or Research.ethics@uts.edu.au and quote this number UTS HREC REF NO. ETH21-6090.

Do you agree to be part of this research and the research data gathered from this survey to be published in a form that does not identify you?

Please select one response.

- Yes
- No

Pureprofile 0%

What is your current role?

Please select one response.

- Radiation therapist
- Radiation oncologist
- Medical physicist
- Other (Please specify)

NEXT >

Pureprofile 2%

Where did you receive your professional training as a **medical physicist**?

Please select one response.

- Australia
- New Zealand
- Other (Please specify)

NEXT >

Pureprofile 4%

In the following section, we are interested in understanding which factors are most important to you when thinking about the application of AI in your work tasks related to radiation therapy treatment planning.

Background
AI refers to the simulation of human intelligence by a system or a machine. AI can enable the automation of tasks in radiotherapy such as image reconstruction, image registration and segmentation, clinical decision support, treatment planning and quality assurance. The successful integration of AI enabled treatment planning in radiation therapy requires understanding of end users' perceptions and attitudes.

Before starting the survey, please read the following information, which explains the aspects of AI systems you will be asked to consider when making the choices. For the purposes of this study, we will ask you to consider only the AI-system features described in this survey when making your choice in each scenario.

NEXT >

Pureprofile 6%

Imagine that your health care facility is considering implementing an AI system that will facilitate radiation therapy planning. The differences between the AI systems can be described in terms of the following attributes:

- **Accuracy of contouring healthy organs**: Degree of precision and correctness of the AI system output compared to manually contoured healthy organs
- **Automation:** 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:** The ability of AI to provide understandable, transparent, and trustworthy explanations for its decisions or actions.
- **Compatibility with other systems:** Different approaches to connecting and integrating AI with other systems or applications.
- **AI impact on workload**: The impact of AI on the time required for generating treatment plans (dosimetry) compared with a predominantly human-based system

NEXT >

Pureprofile 8%

You will first see a practice scenario showing two different AI systems, each characterised by the attributes presented earlier and asked to choose the system you prefer. In this practice scenario only we will rephrase your choice and ask you to confirm your choice.

You will then be asked to choose between the two systems on 12 different occasions. You will then be asked whether you prefer your chosen system or a human-based system. Each time, please read all of the information on the page before you make your choice.

Some of the terms are highlighted in blue – hover your mouse or pointer over the highlighted words if you want to see more information about those terms.

There are no right or wrong answers to the next set of questions, your answers will give us very important information that will help guide health care practices.

NEXT >

Pureprofile 10%

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	**Improved contouring precision** compared with manual organ contouring	**Reduced contouring precision** compared with manual organ contouring
Automation	**Assistive system** Requires clinician verification and sign-off	**Assistive system** Requires clinician verification and sign-off
Explanatory ability	**In-depth explanations** of AI reasoning and decisions	**"Black box" with no 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	60 minutes **saved** per patient	No change
Which system do you prefer?	○	○

NEXT >

Pureprofile 12%

For this initial question only, you prefer a system that is more accurate, saves 60 minutes per patient, with detailed explanations for how the decisions were arrived at and which is seamlessly integrated into the existing system to one that has worse accuracy, doesn't have any time-savings, with no insight into how the decision was made and that requires manual exporting and importing of information. Is that right?

Please select one response.

- Yes
- No

NEXT >

Pureprofile 14%

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

Please select one response.

- Yes
- No

NEXT >

Pureprofile 16%

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	**Improved contouring precision** compared with manual organ contouring
Automation	**Autonomous system**	**Assistive system** Requires clinician verification and sign-off
Explanatory ability	**In-depth explanations** of AI reasoning and decisions	**In-depth explanations** of AI reasoning and decisions
Compatibility with other systems	**Separate system to the existing software and systems**	**Fully integrated system with existing software and systems**
AI impact on workload	30 minutes **longer** per patient	30 minutes **saved** per patient
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

NEXT >

Pureprofile 21%

You're viewing task 2 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	**Same contouring precision** as manual organ contouring	**Improved contouring precision** compared with manual organ contouring
Automation	**Assistive system** Requires clinician verification and sign-off	**Autonomous system**
Explanatory ability	**"Black box" with no explanations** of AI reasoning and decisions	**Basic explanations** of AI reasoning and decisions
Compatibility with other systems	**Separate system to the existing software and systems**	**Separate system to the existing software and systems**
AI impact on workload	30 minutes **saved** 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

NEXT >

Pureprofile 25%

You're viewing task 3 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	**Same contouring precision** as manual organ contouring	**Same contouring precision** as 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	**In-depth 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	60 minutes **saved** 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

NEXT >

Pureprofile 29%

You're viewing task 4 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	**Same contouring precision** as manual organ contouring
Automation	**Autonomous system**	**Autonomous system**
Explanatory ability	**"Black box" with no explanations** of AI reasoning and decisions	**In-depth explanations** of AI reasoning and decisions
Compatibility with other systems	**Separate system to the existing software and systems**	**Fully integrated system with existing software and systems**
AI impact on workload	30 minutes **saved** per patient	60 minutes **saved** per patient
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

instructions

NEXT >

Pureprofile 33%

You're viewing task 5 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	**Same contouring precision** as manual organ contouring
Automation	**Autonomous system**	**Autonomous system**
Explanatory ability	**In-depth 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	60 minutes **saved** per patient	30 minutes **saved** per patient
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

NEXT >

Pureprofile 36%

You're viewing task 6 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	**Improved 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	**Separate system to the existing software and systems**	**Fully integrated system with existing software and systems**
AI impact on workload	60 minutes **saved** per patient	30 minutes **longer** per patient
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

NEXT >

Pureprofile

40%

You're viewing task 7 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	**Improved contouring precision** compared with manual organ contouring	**Same contouring precision** as manual organ contouring
Automation	**Autonomous system**	**Assistive system** Requires clinician verification and sign-off
Explanatory ability	**Basic explanations** of AI r	**"Black box" with no explanations** of AI asoning and decisions
Compatibility with other systems	**Separate syst**	**stem to the existing software and systems**
AI impact on workload	30 minutes **saved** per patient	No change
Which system do you prefer?	○	○

Providing a comprehensive summary of AI reasoning but no explanation of its algorithm and data sources it used

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

Please select one response.

Yes

No

NEXT >

Pureprofile 44%

You're viewing task 8 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	**Improved contouring precision** compared with manual organ contouring
Automation	**Autonomous system**	**Assistive system** Requires clinician verification and sign-off
Explanatory ability	**In-depth explanations** of AI reasoning and decisions	**Basic explanations** of AI reasoning and decisions
Compatibility with other systems	**Separate system to the existing software and systems**	**Fully integrated system with existing software and systems**
AI impact on workload	30 minutes **longer** per patient	30 minutes **longer** per patient
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

NEXT >

Pureprofile 48%

You're viewing task 9 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	**Same contouring precision** as manual organ contouring	**Improved contouring precision** compared with manual organ contouring
Automation	**Autonomous system**	**Assistive system** Requires clinician verification and sign-off
Explanatory ability	**Basic explanations** of AI reasoning and decisions	**In-depth 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	No change	30 minutes **longer** per patient
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

NEXT >

Pureprofile 52%

You're viewing task 10 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	**Improved contouring precision** compared with manual organ contouring	**Same contouring precision** as manual organ contouring
Automation	**Assistive system** Requires clinician verification and sign-off	**Autonomous system**
Explanatory ability	**"Black box" with no explanations** of AI reasoning and decisions	**In-depth 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	30 minutes **longer** per patient
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

NEXT >

Pureprofile 56%

You're viewing task 11 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	**Improved contouring precision** compared with manual organ contouring
Automation	**Assistive system** Requires clinician verification and sign-off	**Autonomous system**
Explanatory ability	**"Black box" with no explanations** of AI reasoning and decisions	**"Black box" with no explanations** of AI reasoning and decisions
Compatibility with other systems	**Separate system to the existing software and systems**	**Fully integrated system with existing software and systems**
AI impact on workload	60 minutes **saved** per patient	30 minutes **longer** per patient
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

NEXT >

Pureprofile 60%

You're viewing task 12 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	**Same contouring precision** as manual organ contouring	**Same contouring precision** as manual organ contouring
Automation	**Autonomous system**	**Assistive system** Requires clinician verification and sign-off
Explanatory ability	**In-depth 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	No change	60 minutes **saved** per patient
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

NEXT >

Pureprofile 60%

You're viewing task 12 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	**Same contouring precision** as manual organ contouring	**Same contouring precision** as manual organ contouring
Automation	**Autonomous system**	**Assistive system** Requires clinician verification and sign-off
Explanatory ability	**In-depth exp** AI system operates without the need for human intervention. It can make decision and execute tasks independently.	**asic explanations** 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	No change	60 minutes **saved** per patient
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

NEXT >

Pureprofile 64%

Please fill out the following rating table about the survey.

Please select one response.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
I found the tasks difficult	○	○	○	○	○
I found it difficult to tell the difference between the options presented	○	○	○	○	○
I considered all features for each system option	○	○	○	○	○

NEXT >

Pureprofile 66%

Were there any attributes which were **always** important in making your choice?

Please select all that apply.

- Accuracy of organ contouring
- Automation
- Explanatory ability
- Compatibility with other systems
- AI impact on workload
- All the above

NEXT >

Pureprofile 68%

Were there any attributes which were **never** important?

Please select all that apply.

- Accuracy of organ contouring
- Automation
- Explanatory ability
- Compatibility with other systems
- AI impact on workload
- None of the above

NEXT >

Pureprofile

70%

Are there any attributes that you find relevant to consider when evaluating AI solutions for radiation therapy treatment planning but were not presented in this survey?

Please type in the box provided.

NEXT >

Appendix 6

Table A6.1: Results of scoping review

Author	Location	Method	N	Population	Concept/Objective	Context
Fischer et al. 2023	Germany	DCE Protocol	NR	Patient with stroke vs general population	To describe the development of a discrete choice experiment (DCE) to weigh criteria that impact patient and public acceptance for DHIs	Stroke
Xie et al 2023	China	DCE	561	General population	To examine the influence of health app attributes and sociodemographic characteristics on consumers' willingness to purchase health apps, and how the value of the health app attributes varies for individuals with different sociodemographic characteristics.	Healthcare
Liu et al. 2021	China	DCE	767	General population	To visualise and measure patients' heterogeneous preferences from various angles of AI diagnosis versus clinicians in the context of the COVID-19 epidemic in China.	COVID-19
Esmaeilzadeh et al. 2020	USA	Survey	307	General population	To examine the perceived benefits and risks of AI medical devices with clinical decision support (CDS) features from consumers' perspectives.	Healthcare
Robertson et al. 2023	USA	DCE	2675	Patients; general population	Tested for the impact (association) of demographic and attitudinal variables (e.g. trust in AI) on preference for AI vs human provider	Leukemia, Sleep apnoea
Poulos et al. 2023	USA	DCE	171	Patients with heart failure	To measure the preferences for use of AI in UL imaging; to examine patients' tolerance for different levels of diagnostic performance in exchange for changes in echo administration and interpretation.	Ultrasound imaging
Parry et al. 2023	USA	Survey	397	Orthopaedic patients	To investigate the patient opinion on the use of Artificial Intelligence (AI) in Orthopaedics.	Orthopaedics
Haan et al. 2019	Netherlands	Semi-structured Interviews	20	Patients	To understanding of the patient's level of knowledge of AI and to explore the meanings patients ascribe to key topics, such as radiology and AI; domains related to patients' perspective on the use of AI in radiology	Radiology
Young et al. 2021	NA	SLR	23 studies	Patients and general population	To investigate attitudes toward clinical AI (either hypothetical or realised),	Healthcare
Richardson et al. 2021	USA	Focus groups	15 focus groups/ 87 participants	General population	To understand how patients view the use of AI in their healthcare; o characterise the range of patient opinions about emerging AI applications in healthcare	Healthcare

Author	Location	Method	N	Population	Concept/Objective	Context
Fritsch et al. 2022	Germany	Question-naire	452	Patients	To investigate the perception of artificial intelligence in healthcare	Healthcare
Khullar et al.2022	USA	Survey	926	General population	To investigate general public attitudes towards application in specific areas (chest x ray, pneumonia, antibiotics, cancer diagnosis, message delivery (telling you that you have cancer); attitude to impact of AI on healthcare	Healthcare
Vo et al. 2023	NA	SLR	105	Patients, General population, HCP	To investigate attitudes toward AI in healthcare	Healthcare
Jeya-kumar et al. 2023	Canada	Semi-structured Interviews	12	Patients	To explore patients' views on what skills they believe health care professionals should have in preparation for this AI-enabled future and how we can better engage patients when adopting and deploying AI technologies in health care settings.	Healthcare
Plough et al. 2021	Danish	Choice based conjoint survey	1027	General population	To investigate the public's preferences for the performance and explainability of AI decision making in health care and determined whether these preferences depend on respondent characteristics, including trust in health and technology and fears and hopes regarding AI	Healthcare
Cinalioglu et al. 2023	Canada	Survey	12052	General population	To explore differences between younger versus older Canadians with regard to the level of comfort and perceptions around the adoption and use of AI in health care settings	Healthcare
Racine et al. 2024	UK Canada	Inter-vuiews	40	HCP and parents	To explore the perspectives of HCPs and parents regarding the use of AI for pain assessment in the NICU	Neonatal intensive care unit (NICU)
Queralt Miró Catalina et al. 2023	Spain	Survey	379	General population	To describe the population's perception and knowledge of the use of AI as a health support tool and its application to radiology	Radiology
Wang et al. 2023	USA	Survey	222	Patients	To examine the factors that affect the motivation of patients with chronic diseases to adopt AI-based home care systems	Chronic diseases
Gould et al. 2023	Australia (st Vincent's Hospital, Melbourne)	Interviews	20	Patients	To explore the understanding and attitudes of patients who underwent knee replacement surgery regarding AI in the context of risk prediction for shared clinical decision-making.	Surgery
Aggraval et al. 2021	UK	Survey	408	Patients	To understand the perspectives and viewpoints of patients regarding the use of their health data in AI research.	Healthcare
Gao et al. 2020	China	Social media post analysis	2315	General population	To explore the public perception of AI in medical care through a content analysis of social media data, including specific topics that the public is concerned about; public attitudes toward AI in medical care and the reasons for them; and public opinion on whether AI can replace human doctors.	Healthcare

Author	Location	Method	N	Population	Concept/Objective	Context
Beets et al. 2023	USA	SLR	11 nationally representative surveys	General population	To investigate public attitudes toward AI in health care and reveals the challenges and opportunities for more effective and inclusive engagement on the use of AI in health settings	Healthcare
Chew et al. 2022	NA	Scoping review	26 studies	Various population	To provide an overview of the perceptions and needs of AI to increase its adoption in health care.	Various context
Couture et al. 2023	Canada	Survey	21	General population and experts	To explore the perspectives and attitudes of citizens and experts regarding the ethics of AI in population health, the engagement of citizens in AI governance, and the potential of a digital app to foster citizen engagement.	Healthcare
Ho et al. 2023	USA	Survey	14	Physicians and patients	To evaluate barriers and facilitators to the implementation of a novel machine learning–based screening tool for PAD among physician and patient stakeholders using the Consolidated Framework for Implementation Research (CFIR).	Cardiology
Hölgyesi et al. 2024	Hungary	WTP	1400	Patients and physicians	To assess social preferences for two different advanced digital health technologies and investigate the contextual dependency of the preferences.	surgery
Stai et al. 2020	USA	Survey	264	General population	To understand better the public perception and comprehension of medical technology such as artificial intelligence (AI) and robotic surgery.	Robotic surgery
Carter et al. 2023	Australia	Focus groups (n=8)	50	Women	To understand women's values regarding the use of AI to read mammograms in breast cancer screening.	Breast cancer screening

Table A6.2: Respondents country of birth: other than Australia and New Zealand (N=533)

Country of birth	Frequency (n, %)
Brazil	1 (<1)
China	9 (1.6)
England	10 (1.8)
Fiji	2 (<1)
Germany	4 (<1)
Hong Kong	1 (<1)
Hungary	1 (<1)
India	5 (<1)
Indonesia	2 (<1)
Ireland	1 (<1)
Latvia	1 (<1)
Lebanon	1 (<1)
Malaysia	2 (<1)
Malta	3 (<1)
Netherlands	1 (<1)
New Caledonia	1 (<1)
Northern Ireland	1 (<1)
Pakistan	2 (<1)
Philippines	3 (<1)
Scotland	4 (<1)
Singapore	1 (<1)
South Africa	3 (<1)
South East Asia	1 (<1)
South Korea	1 (<1)
Sweden	1 (<1)
United Kingdom	5 (<1)
United Arab Emirates	1 (<1)
URUGUAY	1 (<1)
USA	3 (<1)

Figure A6.2: Preferences among Australian general population (Ethics approval)

CHERE
CENTRE FOR HEALTH ECONOMICS RESEARCH AND EVALUATION

UNIVERSITY OF TECHNOLOGY SYDNEY

21 June 2024

Dear Milena,

RE: Use of artificial intelligence (AI) in cancer diagnosis and treatment – Discrete Choice Experiment

At the meeting on 3 May 2024, the CHERE management team agreed that this research project is appropriate to be conducted under CHERE's program ethics approval from the UTS Human Research Ethics Committee (UTS HREC REF NO. 2015000135).

Yours sincerely

Production Note:
Signature removed prior to publication.

Stephena Goodall
Deputy Director, CHERE

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Figure A6.3: Preferences among Australian general population (survey screenshots)

PARTICIPANT INFOMRATION SHEET
USE OF ARTIFICIAL INTELLIGENCE IN CANCER TREATMENT
UTS Human Research Ethics Committee (HREC) APPROVAL REF NO. 2015000135

About this survey:
This research project aims to find out what people think about using artificial intelligence (AI) in healthcare. We would like to understand your opinions about bringing AI into cancer treatment. Your answers will help Australian decision-makers understand what patients value when considering AI for cancer treatment. The survey will take about 15 minutes. We will ask you to imagine some situations and choose your preferred option, then answer some questions about yourself and your opinions.

Who is conducting this research?
This study is being conducted by Milena Lewandowska, Prof Rosalie Viney, and Prof Deborah Street at the Centre for Health Economics Research and Evaluation at the University of Technology Sydney. The research is a part of a PhD (Milena Lewandowska) funded by the Digital Health Collaborative Research Centre (DHCRC). The study has been approved by the University of Technology Sydney [redacted]

Do I have to take part in this research study?
Participation in this study is voluntary. It is completely up to you whether or not you take part. If you decide to take part, please continue with the survey by completing the questions below and clicking on NEXT. If you begin, you can change your mind at any time and stop completing the survey.

Are there any risks/inconvenience?
We don't expect that participation in this questionnaire will cause any harm or discomfort.

What will happen to the information collected?
The survey is anonymous, and your identity can never be linked to your answers. Submission of this online questionnaire is an indication of your consent to the research team collecting and using your answers to the questions for the research project. At the end of this research, we will store the survey data, and it may also be used in other related research. The data will always be treated confidentially. We plan to publish the results of this research in academic journals and reports for medical organisations and health departments.

What if I have concerns or a complaint?
If you have concerns about the research that you think we can help you with, please feel free to contact Rosalie Viney at Rosalie.Viney@uts.edu.au or Milena Lewandowska at Milena.Lewandowska@uts.edu.au. If you would like to talk to someone who is not connected with the research, you may contact the Research Ethics Officer on 02 9514 1793 or Research.ethics@uts.edu.au and quote this number [redacted]

The research data gathered from this survey may be published, but if so it will be in a form that does not identify you. Do you agree to be part of this research?

Please select one response.

Yes

No

What gender do you identify as?

Please select one response.

♂ Male | ♀ Female | Other | Prefer not to say

What is your current age in years?

Please select which range it belongs.

Select one...

In which country were you born?

Please select one response.

- Australia
- New Zealand
- Other (Please specify)
- Prefer not to say

Are you of Aboriginal origin, Torres Strait Islander origin, or both?

Please select one response.

- Aboriginal
- Torres Strait Islander
- Both Aboriginal and Torres Strait Islander
- Neither
- Prefer not to say

What is the highest level of education you have attained ?

Please select one response.

- Did not go to school
- Year 11 and below
- Year 12 or equivalent
- Certificate (any level including trade certificate)
- Diploma/advanced diploma
- Bachelors on honours degree
- Post graduate degree (Masters or Doctorate)
- Prefer not to say

What is your current work status?

Please select one response.

- Employed full-time
- Employed part-time
- Not employed but looking for a job
- Retired
- Home duties
- Not-working student
- Other (please specify)

In general, would you say your health is?

Please select one response.

Excellent	Very Good	Good	Fair	Poor
○	○	○	○	○

Have you ever been told by a doctor or nurse that you have any type of cancer?

Please select one response.

- Yes
- No
- I don't know
- Prefer not to say

Do you feel knowledgeable about cancer treatment and what it entails?

Please select one response.

- Yes
- No

Survey Vignette

In this part, we want to know what you think is most important about using artificial intelligence (AI) for cancer treatment, even if you haven't experienced it yourself. Before completing the questions, here is a brief background of the type of cancer treatment where AI could be used.

Background:
Radiation therapy, also known as radiotherapy, is a common treatment for cancer. It uses radiation to kill cancer cells. An important part of the treatment process involves taking medical images, such as X-rays, of the tumour. These images help doctors aim the radiation precisely to increase its effectiveness and reduce harm to healthy tissue. AI technology enables computers or machines to think and learn similarly to humans. It can perform tasks that usually require human intelligence, such as recognising patterns, solving problems, and making decisions. With AI playing an increasingly important role in cancer treatment, it is important to understand what people think about it. Before you answer the questions, you'll learn about the different features of AI systems you'll need to think about.

For this survey, please focus on the AI features presented below when you make your choices.
Imagine that you were recently diagnosed with cancer, and you need radiation therapy treatment. You have to choose between two treatment centres. Both treatment centres use AI for cancer treatment, but the AI systems used are different. We'll explain the differences between these AI systems using the following features:

- **Accuracy**: The ability of AI systems to correctly identify cancerous or healthy tissues in medical images such as X-rays.
- **Diagnosis and treatment oversight**: The extent to which the AI system makes decisions about treatment or assists clinicians in their decisions.
- **AI impact on out-of-pocket cost**: Your out-of-pocket costs (personal costs not covered by insurance) associated with each visit.
- **AI impact on time to cancer treatment**: The impact of AI system adoption on the time needed to start cancer treatment.
- **AI-driven use of your data**: How AI is using your data such as medical images and health record data to improve its working/performance.

You will first see a practice scenario showing you two different treatment centres, each using AI systems. These systems are characterised by the features we described above. For this practice choice task, you will be asked to choose the treatment centre you prefer. Once you have made that choice, we will rephrase your choice in words so you can see how we would describe each choice you make. You will only see this 'rephrasing' of your choice for the choice task.

You will then be asked to choose between the two treatment centres for 16 different choice tasks. You will then be asked whether you prefer your chosen system or a human-based system after each choice task. Each time, please read all of the information on the page before you make your choice.

Some of the terms you will see describing the AI systems are highlighted in blue – hover your mouse or pointer over the highlighted words if you want to see more information about those terms.

There are no right or wrong answers to the 16 choice tasks, your answers will give us very important information that will help guide health care practices.

Practice choice set

Imagine that you were recently diagnosed with cancer, and you will be treated with radiation therapy treatment. You have a choice between two treatment centres. AI-systems are used for diagnosis and treatment at both treatment centres, but the systems are different. Which treatment centre would you prefer?

Please click on the treatment centre you prefer. Please hover your mouse or pointer over the highlighted words if you want to see more information about those terms.

	Treatment centre A	**Treatment centre B**
Accuracy Compared with clinicians	The AI system sometimes misses cancer	The AI system is less likely to miss cancer and less likely to call healthy tissue for cancer
Diagnosis and treatment oversight	**Assistive**	**Assistive**
AI impact on out-of-pocket costs	Additional $100	No additional costs ($0)
AI impact on time to cancer treatment Compared to the usual 30 days waiting time at treatment centre not using AI it will be	10 days longer	15 days shorter
AI-driven use of your data to update its learning/model	AI uses your medical images and your health record data without needing your consent	The AI may use you medical images only, and only with your consent
Which treatment centre do you prefer?	◯	◯

For this initial question only, you prefer a treatment centre that has worse accuracy, $100 more expensive with longer waiting time to treatment and never asks for your consent before using your medical images and health record data to update its model compared to one that is more accurate, saves $100 out-of-pocket expenses, shortens the waiting time to treatment by 15 days and always asks for your consent before using your medical images to update its model. Is this what you intended?

Please select one response.

- Yes
- No

Compared with the treatment centre you have chosen, would you prefer a treatment centre that does not use AI?

Please select one response.

- Yes
- No

Imagine that you were recently diagnosed with cancer, and you will be treated with radiation therapy treatment. You have a choice between two treatment centres. AI-systems are used for diagnosis and treatment at both treatment centres, but the systems are different. Which treatment centre would you prefer?

Please click on the treatment centre you prefer. Please hover your mouse or pointer over the highlighted words if you want to see more information about those terms.

Task 1 of 16

For testing purpose :
Version - 15
Task - 1

	Treatment centre A	**Treatment centre B**
Accuracy Compared with clinicians	The AI system is less likely to miss cancer and less likely to call healthy tissue for cancer	The AI system sometimes misses cancer
Diagnosis and treatment oversight	**Assistive**	**Fully autonomous**
AI impact on out-of-pocket costs	Additional $35	Additional $50
AI impact on time to cancer treatment Compared to the usual 30 days waiting time at treatment centre not using AI it will be	15 days shorter	10 days longer
AI-driven use of your data to update its learning/model	The AI may use you medical images only, and only with your consent	The AI uses your medical images only, without needing your consent
Which treatment centre do you prefer?	○	○

Compared with the treatment centre you have chosen, would you prefer a treatment centre that does not use AI?

Please select one response.

- Yes
- No

Please select the answer that states "I provide honest answers to surveys" from the list below.

Please select one response.

- I enjoy spending time with friends and family
- I provide honest answers to surveys
- I use public transport to travel for work
- I enjoy travelling to new places
- I shop for food on a weekly basis

Please make sure you pay attention to the questions, or you may be excluded from the survey and lose the right to receive any incentive.

< BACK NEXT >

Please fill out the following rating table about the survey.

Please select one response for each statement.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
I found the tasks difficult	○	○	○	○	○
I found it difficult to tell the difference between the options presented	○	○	○	○	○
I considered all features for each treatment centre	○	○	○	○	○

Were there any attributes which were **always** important in making your choice?

Choose as many as apply here.

- Accuracy
- Diagnosis and treatment oversight
- AI impact on out-of-pocket costs
- AI impact on time to treatment
- AI-driven data usage
- All the above
- None

Were there any attributes which were **never** important?

Choose as many as apply here.

- Accuracy
- Diagnosis and treatment oversight
- AI impact on out-of-pocket costs
- AI impact on time to treatment
- AI-driven data usage
- All the above
- None, all attributes were at least sometimes important

Are there any attributes that you find relevant to consider when considering the use of AI solutions for cancer diagnosis and treatment but were not presented in this survey?

Please type in the box provided.

Please fill out the following rating table about your opinions and attitudes to the potential future adoption of AI in cancer treatment. There are no right or wrong answers.

Please select one response for each statement. radio

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree	Don't know
The benefits of using AI to analyse medical images outweigh the risks						
I would grant permission to use my personal data, such as medical images, to enhance AI systems in radiation therapy planning						
I would be in favour of using AI to interpret medical images as decision support for clinicians						
The implementation of AI may impact my healthcare costs						
AI systems should be tested by an independent authority before they are used on patients						
I would like my physician to override the recommendations of AI if they come to different conclusions based on their experience or knowledge						
I would like to be informed about the use of AI in my diagnosis and treatment process						

If you want to provide any further comments about the questions or survey in general or the answers you provided, please do so below.

Thank you for taking part in this study. We appreciate your help with our research.

Once again, thank you for taking the time to complete this survey. This study is being conducted by researchers at the University of Technology Sydney and is approved by the [redacted]).

If you have any questions or concerns about this survey, please contact [redacted] or the [redacted].

Please click "NEXT >" to submit your survey...

The letter to the editor and the authors response relating to the publication of work presented in Chapter 6 in Value in Health are presented below.

Figure A6.4: The letter to the editor of Value in Health and the authors response

Letter to editor.PDF VIH_Author reply .pdf

Appendix 7

Table A7.1: BWS results: count analysis

Initiative	Best	Worst	MaxDiff	No times each item occurred	Rescaled
19	369	82	287	915	0.31
1	336	116	220	1007	0.22
0	332	136	196	1145	0.17
18	268	117	151	912	0.17
56	262	114	148	913	0.16
41	247	107	140	914	0.15
30	250	115	135	913	0.15
28	258	132	126	914	0.14
31	259	138	121	915	0.13
48	233	113	120	914	0.13
42	259	146	113	913	0.12
39	228	129	99	913	0.11
29	225	138	87	914	0.10
35	258	172	86	913	0.09
14	228	143	85	911	0.09
17	215	130	85	913	0.09
34	238	155	83	913	0.09
51	225	146	79	913	0.09
79	241	148	93	1097	0.08
47	214	137	77	913	0.08
32	223	147	76	914	0.08
21	199	143	56	912	0.06
43	217	161	56	915	0.06
16	236	181	55	914	0.06
23	189	143	46	912	0.05
20	221	176	45	913	0.05
8	192	149	43	912	0.05
54	192	151	41	913	0.04
61	203	164	39	914	0.04
57	199	163	36	914	0.04
44	174	153	21	914	0.02
11	176	159	17	911	0.02
5	174	157	17	959	0.02
64	173	161	12	914	0.01
2	187	179	8	999	0.01
59	165	159	6	912	0.01
69	186	180	6	914	0.01
4	213	209	4	1004	0.00
27	175	174	1	912	0.00
53	181	182	-1	913	0.00
37	189	191	-2	915	0.00
78	186	188	-2	913	0.00
6	190	194	-4	1005	0.00
33	160	168	-8	912	-0.01
58	173	182	-9	913	-0.01
63	171	189	-18	914	-0.02
13	156	175	-19	913	-0.02
25	177	201	-24	914	-0.03
55	166	196	-30	914	-0.03
7	123	154	-31	915	-0.03
76	138	177	-39	914	-0.04
62	146	187	-41	914	-0.04

Initiative	Best	Worst	MaxDiff	No times each item occurred	Rescaled
38	142	184	-42	915	-0.05
22	166	209	-43	915	-0.05
9	138	184	-46	912	-0.05
46	126	173	-47	914	-0.05
52	140	189	-49	913	-0.05
49	143	194	-51	913	-0.06
72	143	197	-54	914	-0.06
60	152	207	-55	914	-0.06
45	123	187	-64	913	-0.07
10	132	199	-67	913	-0.07
15	116	186	-70	912	-0.08
12	125	201	-76	912	-0.08
74	171	248	-77	913	-0.08
75	136	244	-108	1005	-0.11
36	146	248	-102	913	-0.11
65	174	286	-112	913	-0.12
40	122	240	-118	914	-0.13
68	113	233	-120	914	-0.13
73	157	284	-127	913	-0.14
24	137	266	-129	913	-0.14
67	167	297	-130	915	-0.14
50	102	233	-131	914	-0.14
66	149	292	-143	914	-0.16
71	133	277	-144	912	-0.16
3	128	295	-167	912	-0.18
26	113	282	-169	913	-0.19
77	87	305	-218	913	-0.24
70	120	349	-229	913	-0.25

Table A7.2: BWS results based on 15 items ranked as best, 15 items ranked as worst and 15 items ranked as median from the original MNL model with all items and with item 19 used as a base item

Initiative	Description	Mean (SE)
0	Create secure national system for safely sharing health-related documents like clinical notes	0.43 (0.05) ***
1	Make sure information about health care providers and health services is always current and easy to access	0.55 (0.05) ***
2	Assist residential aged care facilities in connecting to the online health record system, My Health Record	0.02 (0.05)
3	Roll out a national newborn enrolment system that connects to government services	-0.48 (0.05) ***
4	Make the use of electronic referrals, transfers of care and discharge summaries business as usual	-0.01 (0.05)
5	Update healthcare provider systems to strengthen and support electronic prescribing	0.02 (0.05)
6	Help aged care software developers to align with My Health Record and the Aged Care Transfer Summary	-0.03 (0.05)
11	Improve digital health skills of the health and care workforce in residential aged care facilities	0.03 (0.05)
14	Make it easier for primary care providers to share information and access data	0.22 (0.05) ***
17	Create accurate terms and standardised rules to ensure systems work well across healthcare settings	0.23 (0.05) ***
18	Set standards for sharing health data with consistent rules to make it easier to share health information across systems	0.4 (0.05) ***
24	Involve consumers in the design and delivery of digital health literacy programs	-0.37 (0.05) ***
26	Undertake research on the effectiveness of digital health literacy programs	-0.48 (0.05) ***
28	Build a system to allow real time sharing of health information safely across care settings nationally	0.33 (0.05) ***

Initiative	Description	Mean (SE)
29	Enable consumers, carers and healthcare providers to access key aged care information in My Health Record	0.23 (0.05) ***
30	Enable key health information to be easily shared to support transfer of care between residential aged care and hospitals	0.36 (0.05) ***
31	Support clinicians and pharmacists to track and manage medicines and prescriptions in real time	0.32 (0.05) ***
33	Develop and expand operational support for electronic prescribing including incident management support	-0.04 (0.05)
35	Add new features to My Health App to better support consumers e.g., electronic prescriptions and test results	0.22 (0.05) ***
36	Involve consumers in improving tools like My Health Record and My Health App	-0.3 (0.05) ***
37	Assist physiotherapists, dietitians, and other allied health providers in sharing their records on My Health Record	-0.02 (0.05)
39	Connect hospital clinical information systems to the National Health Information exchange	0.26 (0.05) ***
40	Allow pregnancy and child health information to be shared and accessed through national digital systems	-0.34 (0.05) ***
41	Improve systems to allow medicines information to be accessed and shared through My Health Record	0.37 (0.05) ***
42	Automatically share information to support multidisciplinary care, including aged care and GP management plans	0.3 (0.05) ***
44	Develop legislation to allow health information sharing across care setting and borders	0.05 (0.05)
48	Ensure provider details in health care provider directories are accurate and kept up to date	0.31 (0.05) ***
50	Evaluate virtual care and policy tools that support team based multidisciplinary care.	-0.38 (0.05) ***
53	Create systems that let healthcare providers to collect and display health information from personal devices securely	-0.02 (0.05)
56	Create better systems to help people access mental health services	0.4 (0.05) ***
58	Improve digital tools to support team-based care for people registered with MyMedicare	-0.04 (0.05)
59	Support development of new digital health standards for emerging technologies	0 (0.05)
64	Develop analysis and governance systems to allow health data to be safely used for health research	0.01 (0.05)
65	Australia to take part in discussion to harmonise global health technology standards and products and to reduce costs	-0.32 (0.05) ***
66	Australia to cooperate internationally to improve secure digital health systems	-0.41 (0.05) ***
67	Ensure Aboriginal and Torres Strait Islander communities can access data held by government and other relevant entities to support local decision making	-0.37 (0.05) ***
68	Support the use of exploratory and simulation research activities to evaluate digital health solutions	-0.35 (0.05) ***
69	Harmonise relevant policy and legislation across jurisdictions to support the secure use of and access to health information	0 (0.05)
70	Get ready for new technologies like AI and genomics in healthcare	-0.65 (0.05) ***
71	Improve national and local digital health systems to allow for use of AI, machine learning, and genomics	-0.41 (0.05) ***
73	Identify healthcare opportunities and risks arising from whole-of economy approaches to regulating AI	-0.37 (0.05) ***
75	Help set up systems for sharing data like genomics and for My Health Record	-0.27 (0.05) ***
77	Participate in evaluations and provide feedback on experiences of digital health	-0.62 (0.05) ***
78	Help consumers and healthcare providers to understand and use digital health to improve care	-0.01 (0.05)

Table AAppendix 7.3: Latent class logit results: comparison of models with 2 classes across different software packages (N=548)

	R studio		Latent Gold		Stata	
Item	**Class 1 (Mean, SE)**	**Class 2 (Mean, SE)**	**Class 1 (Mean, SE)**	**Class 2 (Mean, SE)**	**Class 1 (Mean, SE)**	**Class 2 (Mean, SE)**
Class membership (%)	65.05	34.95	65.38	34.62	65.00	35.00
0	-0.37 (0.09) ***	-0.38 (0.14) **	2.77 (0.12) ***	3.65 (0.19) ***	-0.12	0.32
1	-0.26 (0.09) **	-0.21 (0.15)	2.76 (0.12) ***	3.56 (0.19) ***	-0.01	0.49
2	-0.75 (0.09) ***	-0.89 (0.15) ***	2.02 (0.12) ***	2.72 (0.19) ***	-0.50	-0.18
3	-0.98 (0.1) ***	-2 (0.16) ***	1.6 (0.12) ***	1.38 (0.19) ***	-0.73	-1.30
4	-0.69 (0.09) ***	-1.11 (0.15) ***	1.98 (0.12) ***	2.4 (0.2) ***	-0.44	-0.41
5	-0.78 (0.1) ***	-0.84 (0.15) ***	1.83 (0.12) ***	2.58 (0.19) ***	-0.53	-0.14
6	-0.57 (0.09) ***	-1.42 (0.15) ***	2.02 (0.12) ***	1.85 (0.18) ***	-0.32	-0.72
7	-0.72 (0.1) ***	-1.32 (0.15) ***	1.82 (0.12) ***	1.87 (0.18) ***	-0.47	-0.62
8	-0.6 (0.1) ***	-0.91 (0.15) ***	1.85 (0.12) ***	2.44 (0.19) ***	-0.35	-0.21
9	-0.72 (0.1) ***	-1.48 (0.15) ***	1.7 (0.12) ***	1.56 (0.18) ***	-0.47	-0.78
10	-0.7 (0.1) ***	-1.69 (0.15) ***	1.67 (0.12) ***	1.29 (0.17) ***	-0.45	-0.99
11	-0.51 (0.1) ***	-1.34 (0.15) ***	1.86 (0.11) ***	1.69 (0.17) ***	-0.26	-0.64
12	-0.58 (0.1) ***	-2.02 (0.15) ***	1.72 (0.12) ***	0.91 (0.18) ***	-0.33	-1.32
13	-0.66 (0.1) ***	-1.36 (0.15) ***	1.53 (0.11) ***	1.66 (0.17) ***	-0.41	-0.66
14	-0.63 (0.1) ***	-0.49 (0.15) ***	1.56 (0.11) ***	2.57 (0.17) ***	-0.38	0.21
15	-0.76 (0.1) ***	-1.62 (0.15) ***	1.38 (0.11) ***	1.14 (0.17) ***	-0.51	-0.92
16	-0.59 (0.1) ***	-0.83 (0.15) ***	1.51 (0.12) ***	2.07 (0.19) ***	-0.34	-0.13
17	-0.38 (0.1) ***	-1.03 (0.15) ***	1.72 (0.11) ***	1.68 (0.16) ***	-0.13	-0.33
18	-0.25 (0.1) **	-0.7 (0.15) ***	1.81 (0.11) ***	2.01 (0.17) ***	0.25	0.72
19	Base level	Base level	2.01 (0.11) ***	2.74 (0.17) ***	Base level	Base level
20	-0.73 (0.1) ***	-0.66 (0.15) ***	1.16 (0.11) ***	2.09 (0.18) ***	-0.48	0.04
21	-0.48 (0.1) ***	-1.06 (0.15) ***	1.44 (0.11) ***	1.58 (0.17) ***	-0.22	-0.35
22	-0.68 (0.1) ***	-1.5 (0.15) ***	1.1 (0.11) ***	1.02 (0.16) ***	-0.43	-0.80
23	-0.42 (0.1) ***	-1.26 (0.15) ***	1.39 (0.11) ***	1.22 (0.16) ***	-0.17	-0.56
24	-0.77 (0.1) ***	-2.08 (0.15) ***	0.98 (0.11) ***	0.25 (0.17)	-0.52	-1.38
25	-0.55 (0.1) ***	-1.65 (0.15) ***	1.18 (0.11) ***	0.71 (0.16) ***	-0.30	-0.94
26	-0.77 (0.1) ***	-2.43 (0.16) ***	0.97 (0.11) ***	-0.09 (0.16)	-0.52	-1.73
27	-0.43 (0.1) ***	-1.63 (0.15) ***	1.23 (0.11) ***	0.77 (0.16) ***	-0.18	-0.93
28	-0.55 (0.1) ***	-0.28 (0.15) .	1.08 (0.1) ***	2.02 (0.16) ***	-0.30	0.42
29	-0.53 (0.1) ***	-0.71 (0.15) ***	1.03 (0.1) ***	1.62 (0.15) ***	-0.28	-0.01
30	-0.45 (0.1) ***	-0.42 (0.15) **	1.1 (0.11) ***	1.83 (0.16) ***	-0.19	0.28
31	-0.55 (0.1) ***	-0.3 (0.15) .	0.9 (0.1) ***	1.97 (0.17) ***	-0.30	0.40
32	-0.45 (0.1) ***	-0.96 (0.15) ***	1.01 (0.1) ***	1.21 (0.15) ***	-0.20	-0.26
33	-0.65 (0.1) ***	-1.31 (0.15) ***	0.77 (0.1) ***	0.82 (0.15) ***	-0.40	-0.61
34	-0.5 (0.1) ***	-0.78 (0.15) ***	0.84 (0.1) ***	1.4 (0.16) ***	-0.25	-0.08

Item	R studio		Latent Gold		Stata	
	Class 1 (Mean, SE)	Class 2 (Mean, SE)	Class 1 (Mean, SE)	Class 2 (Mean, SE)	Class 1 (Mean, SE)	Class 2 (Mean, SE)
Class membership (%)	65.05	34.95	65.38	34.62	65.00	35.00
35	-0.73 (0.1) ***	-0.3 (0.15) .	0.6 (0.11) ***	1.81 (0.18) ***	-0.47	0.40
36	-0.82 (0.1) ***	-1.74 (0.16) ***	0.51 (0.11) ***	0.21 (0.16)	-0.57	-1.04
37	-0.76 (0.1) ***	-0.93 (0.15) ***	0.43 (0.1) ***	1.23 (0.16) ***	-0.51	-0.24
38	-0.7 (0.1) ***	-1.45 (0.15) ***	0.55 (0.1) ***	0.52 (0.15)	-0.45	-0.75
39	-0.55 (0.1) ***	-0.51 (0.15) ***	0.64 (0.1) ***	1.45 (0.16) ***	-0.30	0.19
40	-0.9 (0.1) ***	-1.72 (0.16) ***	0.22 (0.1) *	0.25 (0.15)	-0.65	-1.02
41	-0.44 (0.1) ***	-0.42 (0.15) **	0.7 (0.1) ***	1.44 (0.15) ***	-0.19	0.28
42	-0.56 (0.1) ***	-0.41 (0.15) **	0.52 (0.1) ***	1.44 (0.15) ***	-0.31	0.29
43	-0.51 (0.09) ***	-1 (0.15) ***	0.56 (0.1) ***	0.79 (0.15) ***	-0.26	-0.30
44	-0.63 (0.1) ***	-1.05 (0.15) ***	0.4 (0.1) ***	0.72 (0.15) ***	-0.38	-0.35
45	-0.8 (0.1) ***	-1.43 (0.15) ***	0.24 (0.1) **	0.32 (0.15) *	-0.55	-0.73
46	-0.73 (0.1) ***	-1.46 (0.15) ***	0.25 (0.1) **	0.31 (0.15) *	-0.47	-0.76
47	-0.4 (0.1) ***	-1.04 (0.15) ***	0.56 (0.1) ***	0.57 (0.15) ***	-0.15	-0.34
48	-0.45 (0.1) ***	-0.58 (0.15) ***	0.46 (0.1) ***	1.01 (0.15) ***	-0.20	0.13
49	-0.77 (0.1) ***	-1.42 (0.15) ***	0.14 (0.1)	0.17 (0.15)	-0.52	-0.71
50	-0.8 (0.1) ***	-2.05 (0.15)***	0.07 (0.1)	-0.47 (0.15) **	-0.55	-1.35
51	-0.46 (0.1) ***	-0.92 (0.15)***	0.37 (0.1) ***	0.64 (0.15) ***	-0.20	-0.22
52	-0.63 (0.1) ***	-1.68 (0.15)***	0.16 (0.1)	-0.18 (0.15)	-0.38	-0.98
53	-0.62 (0.1) ***	-1.29 (0.15)***	0.11 (0.1)	0.22 (0.15)	-0.37	-0.59
54	-0.44 (0.1) ***	-1.27 (0.15)***	0.29 (0.1) ***	0.16 (0.14)	-0.19	-0.57
55	-0.74 (0.1) ***	-1.29 (0.15)***	-0.04 (0.1)	0.03 (0.14)	-0.49	-0.58
56	-0.4 (0.1) ***	-0.42 (0.15)**	0.24 (0.09) **	0.84 (0.15) ***	-0.15	0.28
57	-0.72 (0.1) ***	-0.77 (0.15)***	-0.1 (0.1)	0.51 (0.14) ***	-0.47	-0.07
58	-0.66 (0.1) ***	-1.25 (0.15)***	-0.1 (0.09)	0.1 (0.14)	-0.41	-0.55
59	-0.48 (0.1) ***	-1.5 (0.15)***	0.04 (0.09)	-0.15 (0.14)	-0.22	-0.80
60	-0.81 (0.1) ***	-1.36 (0.15)***	-0.3 (0.09) ***	0 (0.14)	-0.56	-0.66
61	-0.48 (0.1) ***	-1.2 (0.15)***	0.01 (0.1)	0.06 (0.15)	-0.23	-0.50
62	-0.59 (0.1) ***	-1.67 (0.15)***	-0.15 (0.09)	-0.37 (0.14) *	-0.38	-0.97
63	-0.6 (0.1) ***	-1.48 (0.15)***	-0.2 (0.09)	-0.25 (0.14)	-0.35	-0.78
64	-0.52 (0.1) ***	-1.39 (0.15)***	-0.16 (0.09)	-0.2 (0.14)	-0.27	-0.68
65	-0.56 (0.1) ***	-2.37 (0.15)***	-0.21 (0.09)	-1.11 (0.14) ***	-0.31	-1.67
66	-0.54 (0.1) ***	-2.69 (0.17)***	-0.24 (0.1) **	-1.36 (0.15) ***	-0.29	-1.99
67	-0.8 (0.1) ***	-2.02 (0.16)***	-0.57 (0.09) ***	-0.77 (0.15) ***	-0.55	-1.32
68	-0.73 (0.1) ***	-2.1 (0.15)***	-0.49 (0.09) ***	-0.86 (0.14)	-0.48	-1.40
69	-0.6 (0.1) ***	-1.26 (0.14)***	-0.37 (0.09) ***	-0.34 (0.14)	-0.35	-0.56
70	-0.95 (0.1) ***	-2.62 (0.16)***	-0.8 (0.09) ***	-1.37 (0.15) ***	-0.70	-1.92
71	-0.72 (0.1) ***	-2.29 (0.16)***	-0.64 (0.09) ***	-1.1 (0.15) ***	-0.47	-1.59

	R studio		Latent Gold		Stata	
Item	**Class 1 (Mean, SE)**	**Class 2 (Mean, SE)**	**Class 1 (Mean, SE)**	**Class 2 (Mean, SE)**	**Class 1 (Mean, SE)**	**Class 2 (Mean, SE)**
Class membership (%)	65.05	34.95	65.38	34.62	65.00	35.00
72	-0.59 (0.1) ***	-1.81 (0.15)***	-0.47 (0.09) ***	-0.84 (0.14) ***	-0.33	-1.11
73	-0.79 (0.1) ***	-2.04 (0.15)***	-0.78 (0.09) ***	-1 (0.14) ***	-0.53	-1.34
74	-0.62 (0.1) ***	-1.94 (0.15)***	-0.67 (0.09) ***	-0.98 (0.14) ***	-0.37	-1.24
75	-0.86 (0.09) ***	-1.58 (0.15)***	-0.82 (0.09) ***	-0.65 (0.14) ***	-0.61	-0.88
76	-0.63 (0.1) ***	-1.6 (0.15)***	-0.66 (0.09) ***	-0.77 (0.14) ***	-0.38	-0.90
77	-0.97 (0.1) ***	-2.45 (0.15)***	-0.97 (0.09) ***	-1.46 (0.15) ***	-0.72	-1.75
78	-0.6 (0.1) ***	-1.32 (0.15)***	-0.69 (0.09) ***	-0.64 (0.14) ***	-0.3	-0.62
79	-0.47 (0.09) ***	-0.95 (0.14)***	-0.71 (1000)	-0.39 (1000)	-0.221	-0.24

Table A7.4: BWS results: count analysis, MNL model (base case item 19) (N=548); excluding quick completers

Item	Item description	Theme	MNL Mean (SE)
70	Get ready for new technologies like AI and genomics in healthcare	Data-driven	-1.45 (0.08) ***
77	Participate in evaluations and provide feedback on experiences of digital health	Data-driven	-1.41 (0.08) ***
26	Undertake research on the effectiveness of digital health literacy programs	Person-centred	-1.28 (0.08) ***
3	Roll out a national newborn enrolment system that connects to government services	Digitally enabled	-1.27 (0.08) ***
71	Improve national and local digital health systems to allow for use of AI, machine learning, and genomics	Data-driven	-1.2 (0.08) ***
66	Australia to cooperate internationally to improve secure digital health systems	Data-driven	-1.2 (0.08) ***
50	Evaluate virtual care and policy tools that support team based multidisciplinary care.	Inclusive	-1.17 (0.08) ***
24	Involve consumers in the design and delivery of digital health literacy programs	Person-centred	-1.17 (0.08) ***
73	Identify healthcare opportunities and risks arising from whole-of economy approaches to regulating AI	Data-driven	-1.16 (0.08) ***
67	Ensure Aboriginal and Torres Strait Islander communities can access data held by government and other relevant entities to support local decision making	Data-driven	-1.16 (0.08) ***
68	Support the use of exploratory and simulation research activities to evaluate digital health solutions	Data-driven	-1.14 (0.08) ***
40	Allow pregnancy and child health information to be shared and accessed through national digital systems	Person-centred	-1.13 (0.08) ***
65	Australia to take part in discussion to harmonise global health technology standards and products and to reduce costs	Data-driven	-1.12 (0.08) ***
36	Involve consumers in improving tools like My Health Record and My Health App	Person-centred	-1.09 (0.08) ***
75	Help set up systems for sharing data like genomics and for My Health Record	Data-driven	-1.06 (0.07) ***
74	Support and regulate use of new medical technology including bioinformatics, AI and mixed reality in healthcare settings	Data-driven	-1.02 (0.08) ***
12	Develop guidelines and resources for digital health learning, education and practice	Digitally enabled	-1.01 (0.08) ***

Item	Item description	Theme	MNL Mean (SE)
15	Build digital tools that support healthcare providers in their training and career paths	Digitally enabled	-1.01 (0.08) ***
10	Develop a framework to help organisations ensure their health workforce is digital health ready	Digitally enabled	-0.99 (0.08) ***
45	Implement systems to store and manage healthcare provider details	Person-centred	-0.98 (0.08) ***
60	Align digital health plans and activities across national, state, territory Closing the Gap Implementation Plans	Inclusive	-0.95 (0.08) ***
72	Monitor and identify emerging data sources and technology that support healthcare	Data-driven	-0.95 (0.08) ***
49	Provide digital tools to support expanded delivery of home-based care	Inclusive	-0.95 (0.08) ***
52	Develop and design ways to support the sharing of health information from personal devices	Inclusive	-0.94 (0.08) ***
9	Implement the National Digital Health Capability Action Plan	Digitally enabled	-0.94 (0.08) ***
46	Progress integration between the national digital identity solution and healthcare systems	Person-centred	-0.93 (0.08) ***
22	Require electronic prescribing for expensive or high-risk medicines by updating technology and rules	Digitally enabled	-0.92 (0.08) ***
62	Research and share information about digital health care to help translate new models into clinical practice	Data-driven	-0.91 (0.08) ***
38	Implement unique national healthcare identifiers for individuals and healthcare providers	Person-centred	-0.91 (0.08) ***
76	Measure, monitor and report on changes in digital health to help plan for the future	Data-driven	-0.91 (0.08) ***
55	Create rules and plans to safely use personal devices for sharing health information	Inclusive	-0.89 (0.08) ***
7	Standardise clinical information systems for residential aged care facilities	Digitally enabled	-0.89 (0.08) ***
25	Work with consumers to design health tools that are easy to use and accessible	Person-centred	-0.88 (0.08) ***
13	Create an online platform to share and connect digital resources for the health workforce	Digitally enabled	-0.86 (0.08) ***
63	Collect and share patient reported experience and outcomes data to improve healthcare	Data-driven	-0.86 (0.08) ***
33	Develop and expand operational support for electronic prescribing including incident management support	Person-centred	-0.83 (0.08) ***
58	Improve digital tools to support team-based care for people registered with MyMedicare	Inclusive	-0.83 (0.08) ***
6	Help aged care software developers to align with My Health Record and the Aged Care Transfer Summary	Digitally enabled	-0.82 (0.07) ***
53	Create systems that let healthcare providers to collect and display health information from personal devices securely	Inclusive	-0.81 (0.08) ***
37	Assist physiotherapists, dietitians, and other allied health providers in sharing their records on My Health Record	Person-centred	-0.81 (0.08) ***
78	Help consumers and healthcare providers to understand and use digital health to improve care	Data-driven	-0.81 (0.08) ***
4	Make the use of electronic referrals, transfers of care and discharge summaries business as usual	Digitally enabled	-0.8 (0.07) ***
27	Make digital health literacy part of national safety and quality standards	Person-centred	-0.8 (0.08) ***
59	Support development of new digital health standards for emerging technologies	Inclusive	-0.79 (0.08) ***
69	Harmonise relevant policy and legislation across jurisdictions to support the secure use of and access to health information	Data-driven	-0.79 (0.08) ***

Item	Item description	Theme	MNL Mean (SE)
64	Develop analysis and governance systems to allow health data to be safely used for health research	Data-driven	-0.78 (0.08) ***
2	Assist residential aged care facilities in connecting to the online health record system, My Health Record	Digitally enabled	-0.77 (0.07) ***
5	Update healthcare provider systems to strengthen and support electronic prescribing	Digitally enabled	-0.77 (0.07) ***
11	Improve digital health skills of the health and care workforce in residential aged care facilities	Digitally enabled	-0.76 (0.08) ***
44	Develop legislation to allow health information sharing across care setting and borders	Person-centred	-0.74 (0.08) ***
57	Make it easier to share information between the health and disability systems	Inclusive	-0.71 (0.08) ***
61	Involve consumers who face barriers in using healthcare, and health and community groups, in design of digital health tools	Inclusive	-0.69 (0.08) ***
54	Develop guidelines to support the sharing of health information from personal devices with healthcare providers	Inclusive	-0.69 (0.08) ***
20	Develop a national system for online requests for blood tests and X-rays	Digitally enabled	-0.68 (0.08) ***
8	Improve and update advance care planning documents to support end-of-life decisions and ongoing care preferences	Digitally enabled	-0.68 (0.08) ***
23	Improve digital systems to collect, analyse, and use data from national health registries more effectively	Digitally enabled	-0.68 (0.08) ***
43	Support secure information sharing by enhancing authentication services	Person-centred	-0.65 (0.08) ***
16	Modernise platforms like My Health Record to make them faster and easier to use	Digitally enabled	-0.65 (0.08) ***
21	Require new healthcare technology to work well with existing systems	Digitally enabled	-0.64 (0.08) ***
79	Make clinical quality registries more accessible and able to support patient-cantered care	Data-driven	-0.61 (0.07) ***
32	Develop and deliver systems to support electronic prescribing and electronic medicines charts for high risk and high costs medicines	Person-centred	-0.6 (0.08) ***
47	Improve regulatory requirements to manage consent for access and use of patient health information	Person-centred	-0.59 (0.08) ***
51	Build tools to improve and expand virtual care, particularly for remote and rural communities	Inclusive	-0.58 (0.08) ***
34	Establish regulations for private and public healthcare providers to share information with My Health Record by default	Person-centred	-0.57 (0.08) ***
35	Add new features to My Health App to better support consumers e.g., electronic prescriptions and test results	Person-centred	-0.57 (0.08) ***
14	Make it easier for primary care providers to share information and access data	Digitally enabled	-0.57 (0.08) ***
29	Enable consumers, carers and healthcare providers to access key aged care information in My Health Record	Person-centred	-0.56 (0.08) ***
17	Create accurate terms and standardised rules to ensure systems work well across healthcare settings	Digitally enabled	-0.56 (0.08) ***
39	Connect hospital clinical information systems to the National Health Information exchange	Person-centred	-0.53 (0.08) ***
42	Automatically share information to support multidisciplinary care, including aged care and GP management plans	Person-centred	-0.49 (0.08) ***
48	Ensure provider details in health care provider directories are accurate and kept up to date	Person-centred	-0.48 (0.08) ***
31	Support clinicians and pharmacists to track and manage medicines and prescriptions in real time	Person-centred	-0.46 (0.08) ***
28	Build a system to allow real time sharing of health information safely across care settings nationally	Person-centred	-0.45 (0.08) ***

Item	Item description	Theme	MNL Mean (SE)
30	Enable key health information to be easily shared to support transfer of care between residential aged care and hospitals	Person-centred	-0.43 (0.08) ***
41	Improve systems to allow medicines information to be accessed and shared through My Health Record	Person-centred	-0.42 (0.08) ***
56	Create better systems to help people access mental health services	Inclusive	-0.39 (0.08) ***
18	Set standards for sharing health data with consistent rules to make it easier to share health information across systems	Digitally enabled	-0.38 (0.08) ***
0	Create secure national system for safely sharing health-related documents like clinical notes	Digitally enabled	-0.36 (0.07) ***
1	Make sure information about health care providers and health services is always current and easy to access	Digitally enabled	-0.24 (0.07) **

***p < 0.001;

Table A7.5: Subgroup analyses

Item	Mean (SE)					
	HCP (n=52)	**IT (n=52)**	**Women (n=282)**	**Men (n=265)**	**Education (lower) (n=227)**	**Education (higher) (n=320)**
0	-0.66 (0.24) **	-0.44 (0.24) .	-0.38 (0.1) ***	-0.32 (0.1) **	-0.34 (0.1) ***	-0.39 (0.11) ***
1	-1.07 (0.26) ***	-0.37 (0.24)	-0.26 (0.1) *	-0.21 (0.11) *	-0.3 (0.1) **	-0.17 (0.11)
2	-1.27 (0.25) ***	-0.87 (0.24) ***	-0.86 (0.1) ***	-0.67 (0.11) ***	-0.78 (0.1) ***	-0.78 (0.11) ***
3	-1.51 (0.26) ***	-1.25 (0.25) ***	-1.41 (0.11) ***	-1.13 (0.11) ***	-1.45 (0.1) ***	-1.06 (0.11) ***
4	-1.49 (0.25) ***	-0.86 (0.24) ***	-0.89 (0.1) ***	-0.7 (0.11) ***	-1.02 (0.1) ***	-0.55 (0.11) ***
5	-1.32 (0.26) ***	-0.65 (0.24) **	-0.91 (0.11) ***	-0.62 (0.11) ***	-0.85 (0.1) ***	-0.68 (0.11) ***
6	-1.19 (0.25) ***	-0.68 (0.24) **	-0.91 (0.1) ***	-0.72 (0.11) ***	-0.92 (0.1) ***	-0.71 (0.11) ***
7	-1.39 (0.26) ***	-0.74 (0.25) **	-0.93 (0.11) ***	-0.83 (0.11) ***	-0.99 (0.1) ***	-0.78 (0.11) ***
8	-0.96 (0.26) ***	-0.56 (0.25) *	-0.8 (0.11) ***	-0.54 (0.11) ***	-0.77 (0.1) ***	-0.56 (0.11) ***
9	-1.38 (0.26) ***	-0.88 (0.25) ***	-1 (0.11) ***	-0.87 (0.11) ***	-1.06 (0.1) ***	-0.8 (0.11) ***
10	-1.36 (0.26) ***	-0.83 (0.25) ***	-1.11 (0.11) ***	-0.86 (0.11) ***	-1.1 (0.1) ***	-0.87 (0.11) ***
11	-1.15 (0.26) ***	-0.79 (0.24) **	-0.77 (0.11) ***	-0.73 (0.11) ***	-0.89 (0.1) ***	-0.6 (0.11) ***
12	-1.06 (0.26) ***	-0.87 (0.24) ***	-1.14 (0.11) ***	-0.86 (0.11) ***	-1.15 (0.1) ***	-0.86 (0.11) ***
13	-1.31 (0.26) ***	-0.96 (0.25) ***	-0.94 (0.11) ***	-0.75 (0.11) ***	-1.04 (0.1) ***	-0.65 (0.11) ***
14	-0.83 (0.26) **	-0.67 (0.24) **	-0.53 (0.11) ***	-0.59 (0.11) ***	-0.58 (0.1) ***	-0.55 (0.11) ***
15	-1.54 (0.26) ***	-1.02 (0.24) ***	-1.15 (0.11) ***	-0.83 (0.11) ***	-1.08 (0.1) ***	-0.93 (0.11) ***
16	-0.89 (0.26) ***	-0.65 (0.25) **	-0.83 (0.11) ***	-0.45 (0.11) ***	-0.75 (0.1) ***	-0.53 (0.11) ***
17	-0.82 (0.26) **	-0.36 (0.25)	-0.75 (0.11) ***	-0.36 (0.11) ***	-0.71 (0.1) ***	-0.38 (0.11) ***
18	-0.49 (0.26) .	-0.48 (0.24) *	-0.42 (0.11) ***	-0.35 (0.11) **	-0.51 (0.1) ***	-0.23 (0.11) *
20	-1.04 (0.26) ***	-0.88 (0.24) ***	-0.76 (0.11) ***	-0.6 (0.11) ***	-0.74 (0.1) ***	-0.62 (0.11) ***
21	-0.87 (0.26) ***	-0.85 (0.25) ***	-0.74 (0.11) ***	-0.55 (0.11) ***	-0.71 (0.1) ***	-0.57 (0.11) ***
22	-1.5 (0.26) ***	-0.85 (0.25) ***	-1 (0.11) ***	-0.82 (0.11) ***	-1.05 (0.1) ***	-0.77 (0.11) ***
23	-1.41 (0.26) ***	-0.45 (0.25) .	-0.76 (0.11) ***	-0.59 (0.11) ***	-0.87 (0.1) ***	-0.44 (0.11) ***
24	-1.34 (0.26) ***	-1.16 (0.25) ***	-1.25 (0.11) ***	-1.06 (0.11) ***	-1.4 (0.1) ***	-0.9 (0.11) ***
25	-1.12 (0.26) ***	-1.14 (0.25) ***	-0.94 (0.11) ***	-0.8 (0.11) ***	-0.97 (0.1) ***	-0.77 (0.11) ***
26	-1.73 (0.26) ***	-1.36 (0.25) ***	-1.4 (0.11) ***	-1.14 (0.11) ***	-1.41 (0.1) ***	-1.13 (0.11) ***

Item	Mean (SE)					
	HCP (n=52)	IT (n=52)	Women (n=282)	Men (n=265)	Education (lower) (n=227)	Education (higher) (n=320)
27	-1.25 (0.26) ***	-0.61 (0.24) *	-0.86 (0.11) ***	-0.73 (0.11) ***	-0.96 (0.1) ***	-0.61 (0.11) ***
28	-0.5 (0.26) .	-0.71 (0.25) **	-0.51 (0.11) ***	-0.39 (0.11) ***	-0.54 (0.1) ***	-0.35 (0.11) **
29	-1.29 (0.26) ***	-0.69 (0.25) **	-0.71 (0.11) ***	-0.4 (0.11) ***	-0.65 (0.1) ***	-0.46 (0.11) ***
30	-0.79 (0.25) **	-0.36 (0.25)	-0.45 (0.11) ***	-0.39 (0.11) ***	-0.49 (0.1) ***	-0.36 (0.11) **
31	-1.08 (0.26) ***	-0.92 (0.25) ***	-0.52 (0.11) ***	-0.4 (0.11) ***	-0.47 (0.1) ***	-0.45 (0.11) ***
32	-1.12 (0.25) ***	-0.58 (0.25) *	-0.73 (0.11) ***	-0.45 (0.11) ***	-0.75 (0.1) ***	-0.41 (0.11) ***
33	-1.42 (0.26) ***	-0.73 (0.24) **	-1.04 (0.11) ***	-0.6 (0.11) ***	-0.94 (0.1) ***	-0.7 (0.11) ***
34	-0.62 (0.26) *	-0.68 (0.25) **	-0.74 (0.11) ***	-0.38 (0.11) ***	-0.69 (0.1) ***	-0.44 (0.11) ***
35	-1.06 (0.26) ***	-0.56 (0.25) *	-0.6 (0.11) ***	-0.52 (0.11) ***	-0.64 (0.1) ***	-0.49 (0.11) ***
36	-1.23 (0.26) ***	-1.02 (0.25) ***	-1.15 (0.11) ***	-1.02 (0.11) ***	-1.25 (0.1) ***	-0.91 (0.11) ***
37	-1.14 (0.26) ***	-0.68 (0.25) **	-0.96 (0.11) ***	-0.65 (0.11) ***	-0.92 (0.1) ***	-0.68 (0.11) ***
38	-1.63 (0.26) ***	-0.83 (0.25) ***	-1.12 (0.11) ***	-0.7 (0.11) ***	-1.05 (0.1) ***	-0.75 (0.11) ***
39	-0.8 (0.25) **	-0.66 (0.25) **	-0.63 (0.11) ***	-0.42 (0.11) ***	-0.54 (0.1) ***	-0.53 (0.11) ***
40	-1.17 (0.26) ***	-0.77 (0.25) **	-1.11 (0.11) ***	-1.16 (0.11) ***	-1.35 (0.1) ***	-0.88 (0.11) ***
41	-0.52 (0.25) *	-0.09 (0.25)	-0.54 (0.11) ***	-0.28 (0.11) **	-0.54 (0.1) ***	-0.27 (0.11) *
42	-0.98 (0.25) ***	-0.63 (0.25) *	-0.57 (0.11) ***	-0.39 (0.11) ***	-0.44 (0.1) ***	-0.57 (0.11) ***
43	-1.22 (0.26) ***	-0.62 (0.25) *	-0.7 (0.11) ***	-0.59 (0.11) ***	-0.84 (0.1) ***	-0.43 (0.11) ***
44	-1.03 (0.26) ***	-0.61 (0.25) *	-0.85 (0.11) ***	-0.62 (0.11) ***	-0.87 (0.1) ***	-0.6 (0.11) ***
45	-1.57 (0.26) ***	-0.92 (0.25) ***	-1.16 (0.11) ***	-0.78 (0.11) ***	-1.11 (0.1) ***	-0.84 (0.11) ***
46	-1.63 (0.26) ***	-0.85 (0.25) ***	-1.07 (0.11) ***	-0.78 (0.11) ***	-1.05 (0.1) ***	-0.8 (0.11) ***
47	-0.85 (0.25) ***	-0.22 (0.25)	-0.7 (0.11) ***	-0.46 (0.11) ***	-0.72 (0.1) ***	-0.44 (0.11) ***
48	-1.04 (0.26) ***	-0.31 (0.25)	-0.54 (0.11) ***	-0.39 (0.11) ***	-0.53 (0.1) ***	-0.41 (0.11) ***
49	-1.69 (0.26) ***	-0.87 (0.25) ***	-1.13 (0.11) ***	-0.73 (0.11) ***	-1.02 (0.1) ***	-0.86 (0.11) ***
50	-1.47 (0.26) ***	-0.95 (0.25) ***	-1.18 (0.11) ***	-1.14 (0.11) ***	-1.33 (0.1) ***	-0.98 (0.11) ***
51	-0.84 (0.26) **	-0.46 (0.25) .	-0.56 (0.11) ***	-0.6 (0.11) ***	-0.63 (0.1) ***	-0.53 (0.11) ***
52	-1.64 (0.26) ***	-1 (0.25) ***	-1.05 (0.11) ***	-0.82 (0.11) ***	-1.03 (0.1) ***	-0.83 (0.11) ***
53	-1.52 (0.26) ***	-0.64 (0.25) **	-0.91 (0.11) ***	-0.7 (0.11) ***	-0.87 (0.1) ***	-0.75 (0.11) ***
54	-1.34 (0.26) ***	-0.41 (0.25)	-0.91 (0.11) ***	-0.46 (0.11) ***	-0.83 (0.1) ***	-0.55 (0.11) ***
55	-1.51 (0.26) ***	-1.08 (0.25) ***	-0.93 (0.11) ***	-0.85 (0.11) ***	-0.99 (0.1) ***	-0.77 (0.11) ***
56	-0.59 (0.26) *	-0.61 (0.25) *	-0.37 (0.11) ***	-0.4 (0.11) ***	-0.43 (0.1) ***	-0.35 (0.11) **
57	-1.13 (0.26) ***	-0.54 (0.25) *	-0.84 (0.11) ***	-0.57 (0.11) ***	-0.81 (0.1) ***	-0.59 (0.11) ***
58	-0.98 (0.26) ***	-0.71 (0.25) **	-0.94 (0.11) ***	-0.7 (0.11) ***	-0.99 (0.1) ***	-0.63 (0.11) ***
59	-1.2 (0.26) ***	-0.68 (0.24) **	-0.89 (0.11) ***	-0.68 (0.11) ***	-0.92 (0.1) ***	-0.63 (0.11) ***
60	-1.43 (0.26) ***	-0.92 (0.25) ***	-0.98 (0.11) ***	-0.92 (0.11) ***	-1.01 (0.1) ***	-0.89 (0.11) ***
61	-0.57 (0.25) *	-0.5 (0.25) *	-0.64 (0.11) ***	-0.74 (0.11) ***	-0.85 (0.1) ***	-0.51 (0.11) ***
62	-1.35 (0.26) ***	-0.92 (0.25) ***	-1.03 (0.11) ***	-0.78 (0.11) ***	-1.05 (0.1) ***	-0.74 (0.11) ***
63	-1.63 (0.26) ***	-0.59 (0.25) *	-0.93 (0.11) ***	-0.77 (0.11) ***	-0.97 (0.1) ***	-0.73 (0.11) ***
64	-1.21 (0.25) ***	-0.56 (0.25) *	-0.94 (0.11) ***	-0.6 (0.11) ***	-0.9 (0.1) ***	-0.63 (0.11) ***
65	-1.7 (0.26) ***	-0.93 (0.25) ***	-1.17 (0.11) ***	-1.05 (0.11) ***	-1.25 (0.1) ***	-0.96 (0.11) ***

Item	Mean (SE)					
	HCP (n=52)	IT (n=52)	Women (n=282)	Men (n=265)	Education (lower) (n=227)	Education (higher) (n=320)
66	-1.74 (0.26) ***	-0.84 (0.25) ***	-1.42 (0.11) ***	-0.98 (0.11) ***	-1.4 (0.1) ***	-0.97 (0.11) ***
67	-1.31 (0.26) ***	-0.95 (0.25) ***	-1.17 (0.11) ***	-1.15 (0.11) ***	-1.34 (0.1) ***	-0.96 (0.11) ***
68	-1.87 (0.26) ***	-0.82 (0.25) **	-1.39 (0.11) ***	-0.88 (0.11) ***	-1.36 (0.1) ***	-0.87 (0.11) ***
69	-0.94 (0.26) ***	-0.62 (0.25) *	-0.89 (0.11) ***	-0.69 (0.11) ***	-0.98 (0.1) ***	-0.58 (0.11) ***
70	-1.67 (0.26) ***	-1.13 (0.25) ***	-1.72 (0.11) ***	-1.16 (0.11) ***	-1.61 (0.1) ***	-1.26 (0.11) ***
71	-1.52 (0.26) ***	-0.88 (0.25) ***	-1.44 (0.11) ***	-0.95 (0.11) ***	-1.39 (0.1) ***	-0.98 (0.11) ***
72	-1.29 (0.26) ***	-1.01 (0.25) ***	-1.26 (0.11) ***	-0.64 (0.11) ***	-1.07 (0.1) ***	-0.83 (0.11) ***
73	-1.5 (0.26) ***	-1.08 (0.25) ***	-1.39 (0.11) ***	-0.93 (0.11) ***	-1.3 (0.1) ***	-1 (0.11) ***
74	-1.32 (0.26) ***	-0.86 (0.25) ***	-1.19 (0.11) ***	-0.85 (0.11) ***	-1.23 (0.1) ***	-0.77 (0.11) ***
75	-1.71 (0.25) ***	-0.97 (0.24) ***	-1.23 (0.1) ***	-0.87 (0.11) ***	-1.07 (0.1) ***	-1.06 (0.11) ***
76	-1.19 (0.26) ***	-1 (0.25) ***	-1.04 (0.11) ***	-0.77 (0.11) ***	-1.11 (0.1) ***	-0.67 (0.11) ***
77	-1.62 (0.26) ***	-1.26 (0.25) ***	-1.53 (0.11) ***	-1.28 (0.11) ***	-1.6 (0.1) ***	-1.19 (0.11) ***
78	-0.97 (0.25) ***	-0.51 (0.25) *	-0.9 (0.11) ***	-0.71 (0.11) ***	-0.91 (0.1) ***	-0.69 (0.11) ***
79	-1.12 (0.25) ***	-0.82 (0.24) ***	-0.72 (0.1) ***	-0.48 (0.1) ***	-0.63 (0.1) ***	-0.59 (0.11) ***

Figure A7.1: BWS survey (Ethics approval)

UTS Centre for Health Economics Research and Evaluation (CHERE)

13th December 2024

Dear Milena,

RE: National Digital Health Strategy: Best-Worst Scaling Survey

At the meeting in December 2024, the CHERE management team agreed that this research project is appropriate to be conducted under CHERE's program ethics approval from the UTS Human Research Ethics Committee (UTS HREC REF NO. ETH24-9283). This approval will remain valid for a period of 5 years from the date of approval.

Yours sincerely,

Production Note:
Signature removed prior to publication.

Stephen Goodall

PO Box 123 Broadway NSW 2007
Level 5, Building 20, 100 Broadway, Chippendale NSW 2008. Tel + 61 2 9514 4720 Fax + 61 2 9514 4730
http://www.chere.uts.edu.au

Figure A7.2: BWS survey screenshots

What is the research about?
The purpose of this research is to identify which aspects of the National Digital Health Strategy (NDHS) are perceived as most and least important by different groups such as patients, health providers and policy makers. Your responses will be used to provide policymakers in Australia with actionable insights on how to design, improve or scale digital health initiatives that align more closely with the preferences and needs of the Australian population.

Who is conducting this research?
This study is being undertaken by Milena Lewandowska, Prof Rosalie Viney, Prof Deborah Street and Prof Sally Inglis at the University of Technology Sydney. The research is a part of a PhD (Milena Lewandowska) funded by the Digital Health Collaborative Research Centre (DHCRC). The study has been approved by the University of Technology Sydney UTS HREC REF NO. ETH24-9283

Do I have to take part in this research study?
Participation in this study is voluntary. It is completely up to you whether or not you take part. If you decide to take part, please continue with the survey by completing the question below and clicking on NEXT. If you begin, you can change your mind at any time and stop completing the survey.

Are there any risks/inconvenience?
We don't expect that participation in this questionnaire will cause any harm or discomfort.

What will happen to the information collected?
The survey is anonymous, and your identity can never be linked to your answers. Submission of this online questionnaire is an indication of your consent to the research team collecting and using your answers to the questions for the research project. At the end of this research, we will store the survey data, and it may also be used in other related research. The data will always be treated confidentially. We plan to publish the results of this research in academic journals and reports for medical organisations and health departments.

What if I have concerns or a complaint?
If you have concerns about the research that you think we can help you with, please feel free to contact Rosalie Viney at Rosalie.Viney@uts,.edu.au or Milena Lewandowska at Milena.Lewandowska@uts.edu.au. If you would like to talk to someone who is not connected with the research, you may contact the Research Ethics Officer on 02 9514 1793 or Research.ethics@uts.edu.au and quote this number UTS HREC REF NO. ETH24-9283

Research Aim
The aim of this research is to investigate which of the initiatives that are included in the National Digital Health Strategy are important for achieving sustainable, inclusive, and person-centred health outcomes for Australians. The survey is expected to take about 15 minutes to complete. We will ask you 27 questions where you will need to select your most and least preferred options. We will also ask a few questions about yourself and your opinions.

Do you agree to be part of this research and for the results to be published in a form that does not identify you?

Please select one response.

YES

NO

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Please press play button to play the video.

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The National Digital Health Strategy (2023-2028) in Australia aims to improve the quality, safety and efficiency of the healthcare system through integration of digital technologies. The strategy seeks to achieve 4 outcomes for Australia's health system as presented below:

Digitally enabled

Creating health and wellbeing services that are connected, safe, secure and sustainable.

Person-centred

Ensuring Australians are empowered to look after their health and wellbeing and equipped with the right information and tools.

Inclusive

Providing Australians with equitable access to health services, when and where they need them.

Data-driven

Ensuring data is readily available and informs decision making about individuals, communities and national issues.

The strategy includes specific initiatives that outline priority actions, guiding partners in their contributions to its implementation. We will ask you to identify the initiatives you consider most and least important. Your feedback will help policymakers improve digital health initiatives to better meet the needs of Australians.

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Your task in this survey

Please consider the options provided in each section carefully and respond based on your preferences and experiences.

Section 1: We will ask some questions about you and your work

Section 2: We will present 9 choice tasks and ask you to identify the most important and least important initiatives from the National Digital Health Strategy.

Section 3: We will ask some additional questions about you and your work

Section 4: We will present additional 9 choice tasks and ask you to identify the most important and last important initiatives from the National Digital Health Strategy.

Section 5: We will ask some additional questions about you or your work

Section 6: We will present final 9 choice tasks and ask you to identify the most important and last important initiatives from the National Digital Health Strategy.

Section 7: We will be asked some follow-up questions and there is an opportunity for you to provide feedback about the survey or this topic in general

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How old are you?

Please type your age in the box below.

Please indicate your gender:

Please select one response.

Male	Female	Non-binary	Other	Prefer not to say

Were you born in Australia?

Please select one response.

Yes

No

What postcode do you live in?

Please type in your postcode in the box below.

Prefer not to say

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Are you of Aboriginal origin, Torres Strait Islander origin, or both?

Please select one response.

- Aboriginal
- Torres Strait Islander
- Both Aboriginal and Torres Strait Islander
- Neither
- **Prefer not to say**

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What is the highest level of education you have completed?

Please select one response.

- Year 11 and below
- **Year 12 or equivalent**
- Certificate (any level including trade certificate)
- Diploma/advanced diploma
- Bachelors on honours degree
- Post graduate degree (Masters or Doctorate)
- Prefer not to say

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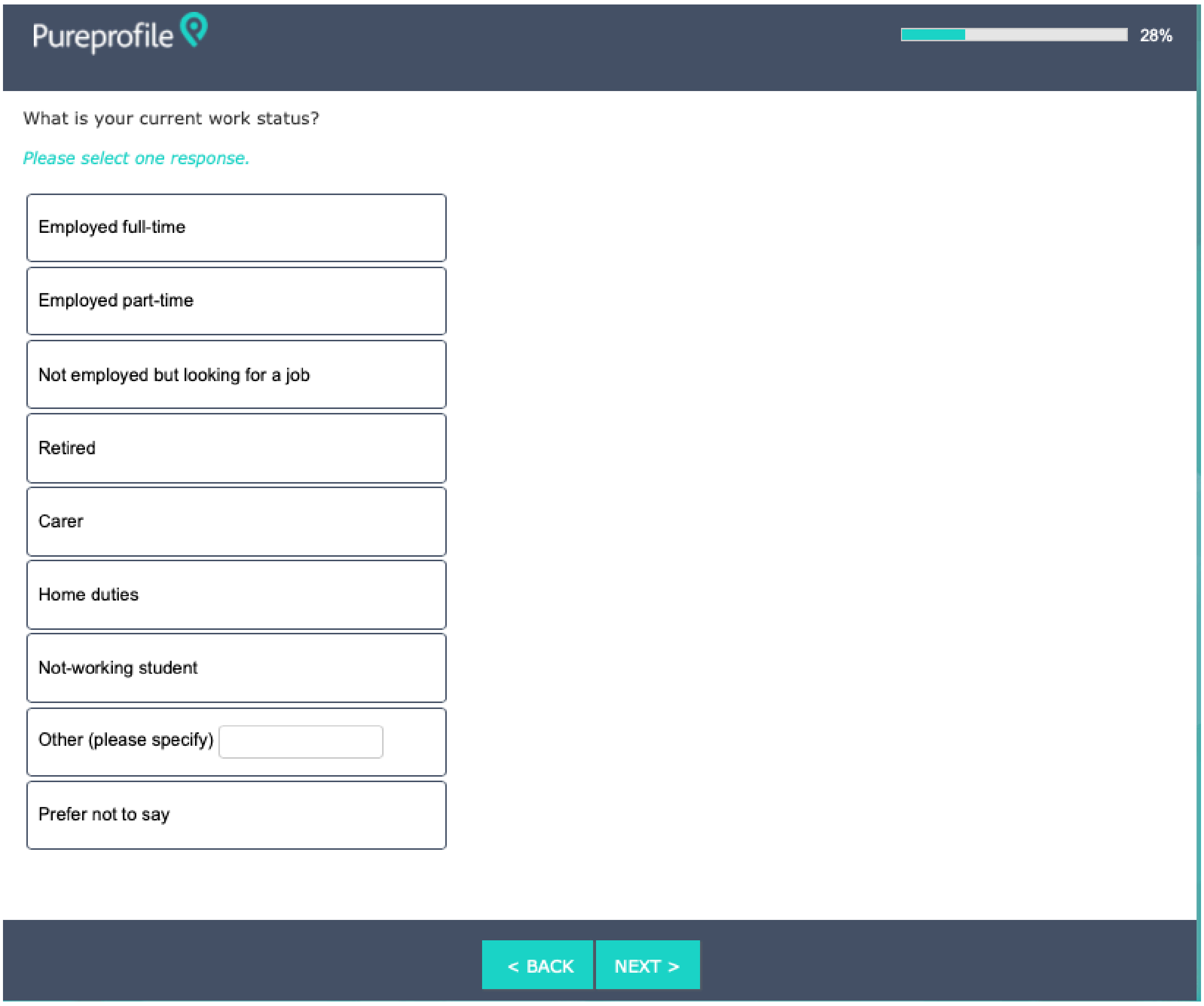
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28%
What is your current work status?
Please select one response.
Employed full-time
Employed part-time
Not employed but looking for a job
Retired
Carer
Home duties
Not-working student
Other (please specify)
Prefer not to say
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29%

Which industry sector do you currently work in, or did you most recently work in?

Please select one response.

- Healthcare
- Finance
- Education
- Manufacturing
- Retail
- Government
- Information Technology (IT)
- Other (please specify)
- Prefer not to say

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Pureprofile

33%

Slide 1 of 5

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is most important to you and which of these initiatives is least important to you. *Please note there are no right or wrong answers here, we are interested in your opinion.*

Most Important	*Task 1 of 27*	Least Important
○	**Assist care homes in connecting to the online health record system, My Health Record**	○
○	**Make it easier for general practitioners (GPs) to share information and access data**	○
○	**Expand online tools to help people record their medical w aged care**	
○	**Build a system to share health information safely across th**	
○	**Combine services for newborns, so parents can register t and access benefits more easier**	

There will be 27 choice tasks in total

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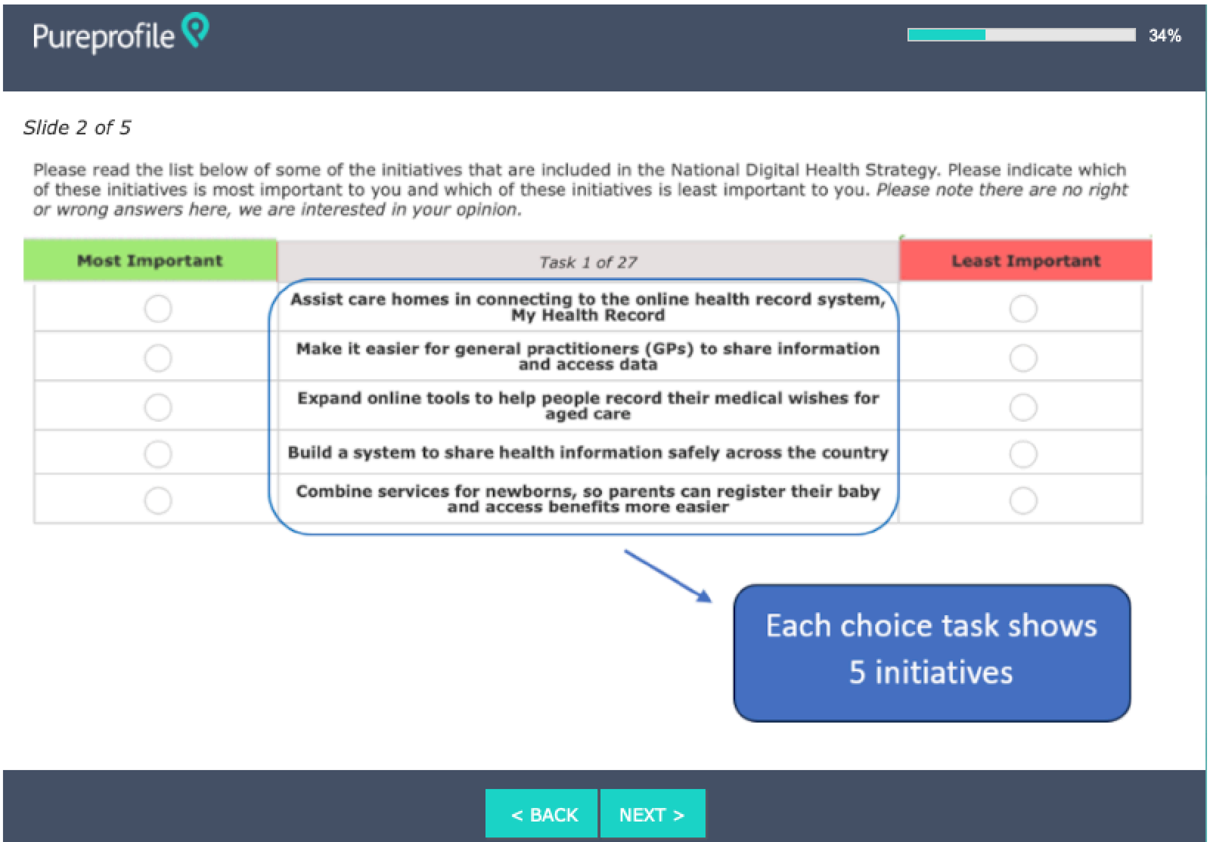
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34%
Slide 2 of 5
Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is most important to you and which of these initiatives is least important to you. Please note there are no right or wrong answers here, we are interested in your opinion.
Most Important
Task 1 of 27
Least Important
Assist care homes in connecting to the online health record system, My Health Record
Make it easier for general practitioners (GPs) to share information and access data
Expand online tools to help people record their medical wishes for aged care
Build a system to share health information safely across the country
Combine services for newborns, so parents can register their baby and access benefits more easier
Each choice task shows 5 initiatives
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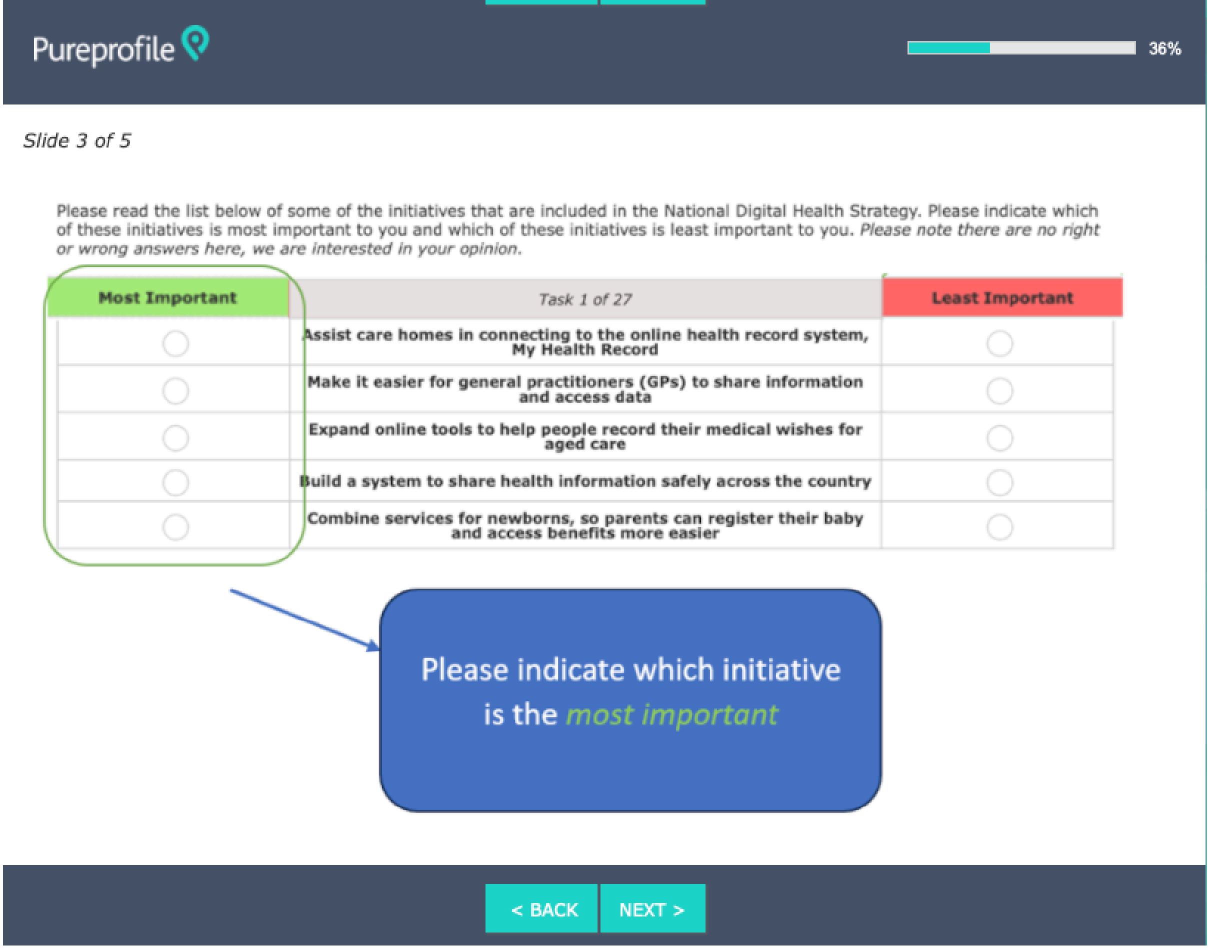
Pureprofile
36%
Slide 3 of 5
Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is most important to you and which of these initiatives is least important to you. Please note there are no right or wrong answers here, we are interested in your opinion.
Most Important
Task 1 of 27
Least Important
Assist care homes in connecting to the online health record system, My Health Record
Make it easier for general practitioners (GPs) to share information and access data
Expand online tools to help people record their medical wishes for aged care
Build a system to share health information safely across the country
Combine services for newborns, so parents can register their baby and access benefits more easier
Please indicate which initiative is the most important
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37%

Slide 4 of 5

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is most important to you and which of these initiatives is least important to you. *Please note there are no right or wrong answers here, we are interested in your opinion.*

Most Important	*Task 1 of 27*	Least Important
○	Assist care homes in connecting to the online health record system, My Health Record	○
○	Make it easier for general practitioners (GPs) to share information and access data	○
○	Expand online tools to help people record their medical wishes for aged care	○
○	Build a system to share health information safely across the country	○
○	Combine services for newborns, so parents can register their baby and access benefits more easier	○

Please indicate which initiative is the *least important*

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Pureprofile

39%

Slide 5 of 5

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is most important to you and which of these initiatives is least important to you. *Please note there are no right or wrong answers here, we are interested in your opinion.*

Most Important	*Task 1 of 27*	Least Important
○	Assist care homes in connecting to the online health record system, My Health Record	○
○	Make it easier for general practitioners (GPs) to share information and access data	○
○	Expand online tools to help people record their medical wishes for aged care	○
○	Build a system to share health information safely across the country	○
○	Combine services for newborns, so parents can register their baby and access benefits more easier	○

For each choice task, You must make both selections to proceed with the survey

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Pureprofile 43%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 1 of 27*	Least Important
◯	**Assist residential aged care facilities in connecting to the online health record system, My Health Record**	◯
◯	**Roll out a national newborn enrolment system that connects to government services**	◯
◯	**Standardise clinical information systems for residential aged care facilities**	◯
◯	**Make it easier for primary care providers to share information and access data**	◯
◯	**Build a system to allow real time sharing of health information safely across care settings nationally**	◯

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Pureprofile 45%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 2 of 27*	Least Important
◯	**Update healthcare provider systems to strengthen and support electronic prescribing**	◯
◯	**Help aged care software developers to align with My Health Record and the Aged Care Transfer Summary**	◯
◯	**Develop a framework to help organisations ensure their health workforce is digital health ready**	◯
◯	**Create accurate terms and standardised rules to ensure systems work well across healthcare settings**	◯
◯	**Support clinicians and pharmacists to track and manage medicines and prescriptions in real time**	◯

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Pureprofile 46%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 3 of 27*	Least Important
◯	**Improve and update advance care planning documents to support end-of-life decisions and ongoing care preferences**	◯
◯	**Implement the National Digital Health Capability Action Plan**	◯
◯	**Create an online platform to share and connect digital resources for the health workforce**	◯
◯	**Develop a national system for online requests for blood tests and X-rays**	◯
◯	**Establish regulations for private and public healthcare providers to share information with My Health Record by default**	◯

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Pureprofile 48%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 4 of 27*	Least Important
◯	**Improve digital health skills of the health and care workforce in residential aged care facilities**	◯
◯	**Develop guidelines and resources for digital health learning, education and practice**	◯
◯	**Modernise platforms like My Health Record to make them faster and easier to use**	◯
◉	**Improve digital systems to collect, analyse, and use data from national health registries more effectively**	◯
◯	**Assist physiotherapists, dietitians, and other allied health providers in sharing their records on My Health Record**	◯

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Pureprofile 50%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 5 of 27*	Least Important
○	**Make it easier for primary care providers to share information and access data**	○
○	**Build digital tools that support healthcare providers in their training and career paths**	○
○	**Protect Health Information and infrastructure against cyber-attacks and natural disasters**	○
○	**Undertake research on the effectiveness of digital health literacy programs**	○
○	**Allow pregnancy and child health information to be shared and accessed through national digital systems**	○

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Pureprofile 51%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 6 of 27*	Least Important
○	**Create accurate terms and standardised rules to ensure systems work well across healthcare settings**	○
○	**Set standards for sharing health data with consistent rules to make it easier to share health information across systems**	○
○	**Require electronic prescribing for expensive or high-risk medicines by updating technology and rules**	○
○	**Enable consumers, carers and healthcare providers to access key aged care information in My Health Record**	○
○	**Support secure information sharing by enhancing authentication services**	○

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Pureprofile 53%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 7 of 27*	Least Important
○	**Develop a national system for online requests for blood tests and X-rays**	○
○	**Require new healthcare technology to work well with existing systems**	○
○	**Work with consumers to design health tools that are easy to use and accessible**	○
○	**Develop and deliver systems to support electronic prescribing and electronic medicines charts for high risk and high costs medicines**	○
○	**Progress integration between the national digital identity solution and healthcare systems**	○

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Pureprofile 55%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 8 of 27*	Least Important
○	**Improve digital systems to collect, analyse, and use data from national health registries more effectively**	○
○	**Involve consumers in the design and delivery of digital health literacy programs**	○
○	**Build a system to allow real time sharing of health information safely across care settings nationally**	○
○	**Add new features to My Health App to better support consumers e.g., electronic prescriptions and test results**	○
○	**Provide digital tools to support expanded delivery of home-based care**	○

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Pureprofile 56%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 9 of 27*	Least Important
○	**Undertake research on the effectiveness of digital health literacy programs**	○
○	**Make digital health literacy part of national safety and quality standards**	○
○	**Support clinicians and pharmacists to track and manage medicines and prescriptions in real time**	○
○	**Implement unique national healthcare identifiers for individuals and healthcare providers**	○
○	**Develop and design ways to support the sharing of health information from personal devices**	○

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Pureprofile 56%

How often do you typically visit a general practitioner (GP)?

Please select one response.

- Weekly
- Monthly
- Every 3-6 months
- Annually
- Rarely/Never
- Prefer not to say

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Pureprofile

57%

In the last 12 months, have you/or your family visited an emergency department (ED)?

Please select one response.

- Yes
- No
- Prefer not to say

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Pureprofile

57%

In the last 12 months, have you/or your family been admitted to hospital?

Please select one response.

- Yes
- No
- Prefer not to say

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Pureprofile

57%

Do you currently have any diagnosed chronic health conditions?

Please select one response.

- Yes
- No
- Prefer not to say

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Pureprofile 59%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 11 of 27*	Least Important
◯	**Enable consumers, carers and healthcare providers to access key aged care information in My Health Record**	◯
◯	**Enable key health information to be easily shared to support transfer of care between residential aged care and hospitals**	◯
◯	**Establish regulations for private and public healthcare providers to share information with My Health Record by default**	◯
◯	**Improve systems to allow medicines information to be accessed and shared through My Health Record**	◯
◯	**Create rules and plans to safely use personal devices for sharing health information**	◯

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Pureprofile 61%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 12 of 27*	Least Important
◯	**Develop and deliver systems to support electronic prescribing and electronic medicines charts for high risk and high costs medicines**	◯
◯	**Develop and expand operational support for electronic prescribing including incident management support**	◯
◯	**Assist physiotherapists, dietitians, and other allied health providers in sharing their records on My Health Record**	◯
◯	**Develop legislation to allow health information sharing across care setting and borders**	◯
◯	**Improve digital tools to support team-based care for people registered with MyMedicare**	◯

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Pureprofile 63%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	Task 13 of 27	Least Important
○	**Add new features to My Health App to better support consumers e.g., electronic prescriptions and test results**	○
○	**Involve consumers in improving tools like My Health Record and My Health App**	○
○	**Allow pregnancy and child health information to be shared and accessed through national digital systems**	○
○	**Improve regulatory requirements to manage consent for access and use of patient health information**	○
○	**Involve consumers who face barriers in using healthcare, and health and community groups, in design of digital health tools**	○

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Pureprofile 64%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	Task 14 of 27	Least Important
○	**Implement unique national healthcare identifiers for individuals and healthcare providers**	○
○	**Connect hospital clinical information systems to the National Health Information exchange**	○
○	**Support secure information sharing by enhancing authentication services**	○
○	**Evaluate virtual care and policy tools that support team based multidisciplinary care.**	○
○	**Develop analysis and governance systems to allow health data to be safely used for health research**	○

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Pureprofile 66%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 15 of 27*	Least Important
○	**Improve systems to allow medicines information to be accessed and shared through My Health Record**	○
●	**Automatically share information to support multidisciplinary care, including aged care and GP management plans**	○
○	**Progress integration between the national digital identity solution and healthcare systems**	○
○	**Create systems that let healthcare providers to collect and display health information from personal devices securely**	○
○	**Ensure Aboriginal and Torres Strait Islander communities can access data held by government and other relevant entities to support local decision making**	●

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Pureprofile 68%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 16 of 27*	Least Important
○	**Develop legislation to allow health information sharing across care setting and borders**	○
●	**Implement systems to store and manage healthcare provider details**	○
○	**Provide digital tools to support expanded delivery of home-based care**	●
○	**Create better systems to help people access mental health services**	○
○	**Get ready for new technologies like AI and genomics in healthcare**	○

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Pureprofile 69%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 17 of 27*	Least Important
○	**Improve regulatory requirements to manage consent for access and use of patient health information**	○
○	**Ensure provider details in health care provider directories are accurate and kept up to date**	○
○	**Develop and design ways to support the sharing of health information from personal devices**	○
○	**Support development of new digital health standards for emerging technologies**	○
○	**Identify healthcare opportunities and risks arising from whole-of economy approaches to regulating AI**	○

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Pureprofile 71%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 18 of 27*	Least Important
●	**Evaluate virtual care and policy tools that support team based multidisciplinary care.**	
○	**Build tools to improve and expand virtual care, particularly for remote and rural communities**	○
○	**Create rules and plans to safely use personal devices for sharing health information**	○
○	**Research and share information about digital health care to help translate new models into clinical practice**	○
○	**Measure, monitor and report on changes in digital health to help plan for the future**	○

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Pureprofile 73%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 19 of 27*	Least Important
○	**Create systems that let healthcare providers to collect and display health information from personal devices securely**	○
○	**Develop guidelines to support the sharing of health information from personal devices with healthcare providers**	○
	Improve digital tools to support team-based care for people registered with MyMedicare	●
●	**Australia to take part in discussion to harmonise global health technology standards and products and to reduce costs**	
○	**Make clinical quality registries more accessible and able to support patient-cantered care**	○

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Pureprofile 73%

Which of the following digital health tools have you used (if any):

Please select all that apply.

My Health Record	Telehealth services (e.g., online consultations)	Electronic prescription	Doctor finders (e.g., HotDoc)	Digital mental health tools (e.g., My Compass, Mind Spot)
Patient portals & Digital Front Door (i.e. a single access point to healthcare services)	Biosensors (e.g., continuous glucose monitors)	ECG monitors with digital health apps	Pacemaker with digital health app	Fitness/diet monitoring
Menstrual cycle tracking	Other (Please specify)	None		

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Pureprofile 73%

How often do you use digital health applications?

Please select one response.

- Every day
- Once a week
- Once a month
- Few times a year
- Never
- Prefer not to say

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Pureprofile 75%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 20 of 27*	Least Important
○	**Make sure information about health care providers and health services is always current and easy to access**	○
○	**Create better systems to help people access mental health services**	○
○	**Make it easier to share information between the health and disability systems**	○
○	**Involve consumers who face barriers in using healthcare, and health and community groups, in design of digital health tools**	○
○	**Support the use of exploratory and simulation research activities to evaluate digital health solutions**	○

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Pureprofile 77%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 21 of 27*	Least Important
○	**Make the use of electronic referrals, transfers of care and discharge summaries business as usual**	○
○	**Support development of new digital health standards for emerging technologies**	○
○	**Align digital health plans and activities across national, state, territory Closing the Gap Implementation Plans**	○
○	**Develop analysis and governance systems to allow health data to be safely used for health research**	○
○	**Improve national and local digital health systems to allow for use of AI, machine learning, and genomics**	○

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Pureprofile 78%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 22 of 27*	Least Important
○	**Standardise clinical information systems for residential aged care facilities**	○
○	**Research and share information about digital health care to help translate new models into clinical practice**	○
○	**Collect and share patient reported experience and outcomes data to improve healthcare**	○
○	**Ensure Aboriginal and Torres Strait Islander communities can access data held by government and other relevant entities to support local decision making**	○
○	**Support and regulate use of new medical technology including bioinformatics, AI and mixed reality in healthcare settings**	○

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Pureprofile

80%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 23 of 27*	Least Important
○	**Develop a framework to help organisations ensure their health workforce is digital health ready**	○
○	**Australia to take part in discussion to harmonise global health technology standards and products and to reduce costs**	○
○	**Australia to cooperate internationally to improve secure digital health systems**	○
○	**Get ready for new technologies like AI and genomics in healthcare**	○
○	**Participate in evaluations and provide feedback on experiences of digital health**	○

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Pureprofile

82%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 24 of 27*	Least Important
○	**Help aged care software developers to align with My Health Record and the Aged Care Transfer Summary**	○
○	**Create an online platform to share and connect digital resources for the health workforce**	○
○	**Support the use of exploratory and simulation research activities to evaluate digital health solutions**	○
○	**Harmonise relevant policy and legislation across jurisdictions to support the secure use of and access to health information**	○
○	**Identify healthcare opportunities and risks arising from whole-of economy approaches to regulating AI**	○

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Pureprofile 83%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 25 of 27*	Least Important
○	**Assist residential aged care facilities in connecting to the online health record system, My Health Record**	○
○	**Modernise platforms like My Health Record to make them faster and easier to use**	○
○	**Improve national and local digital health systems to allow for use of AI, machine learning, and genomics**	○
○	**Monitor and identify emerging data sources and technology that support healthcare**	○
○	**Measure, monitor and report on changes in digital health to help plan for the future**	○

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Pureprofile 85%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 26 of 27*	Least Important
○	**Update healthcare provider systems to strengthen and support electronic prescribing**	○
○	**Protect Health Information and infrastructure against cyber-attacks and natural disasters**	○
○	**Support and regulate use of new medical technology including bioinformatics, AI and mixed reality in healthcare settings**	○
○	**Help set up systems for sharing data like genomics and for My Health Record**	○
○	**Make clinical quality registries more accessible and able to support patient-cantered care**	○

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Pureprofile 87%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 27 of 27*	Least Important
◯	**Make sure information about health care providers and health services is always current and easy to access**	◯
◯	**Improve and update advance care planning documents to support end-of-life decisions and ongoing care preferences**	◯
◯	**Require electronic prescribing for expensive or high-risk medicines by updating technology and rules**	◯
◯	**Participate in evaluations and provide feedback on experiences of digital health**	◯
◯	**Help consumers and healthcare providers to understand and use digital health to improve care**	◯

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Pureprofile 89%

Please read the list below of some of the initiatives that are included in the National Digital Health Strategy. Please indicate which of these initiatives is **most important** to you and which of these initiatives is **least important** to you. There are no right or wrong answers here, we are interested in your opinion.

Most Important	*Task 28 of 27*	Least Important
◯	**Create secure national system for safely sharing health-related documents like clinical notes**	◯
◯	**Make the use of electronic referrals, transfers of care and discharge summaries business as usual**	◯
◯	**Help aged care software developers to align with My Health Record and the Aged Care Transfer Summary**	◯
◯	**Improve digital health skills of the health and care workforce in residential aged care facilities**	◯
◯	**Work with consumers to design health tools that are easy to use and accessible**	◯

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Pureprofile 89%

Please fill out the following rating table about the survey.

Please select one response for each statement.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree
I found the tasks difficult	◯	◯	◯	◯	◯
I found it difficult to tell the difference between the options presented	◯	◯	◯	◯	◯
I considered all options	◯	◯	◯	◯	◯

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Pureprofile 91%

To what extent do you agree with the following statement:

Please select one response for each statement.

	Way too many	Too many	Just right	Too few	Way too few
The number of choice tasks was:	○	○	○	○	○

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Pureprofile 92%

To what extent do you agree with the following statements:

Please select one response for each statement.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree	Don't know
I am generally open to adopting new technologies	○	○	○	○	○	○
Digital health tools can be trusted	○	○	○	○	○	○

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Pureprofile 94%

To what extent do you agree with the following statements:

Please select one response for each statement.

	Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly Agree	Don't know
It is important to make health services safe, secure, and connected	○	○	○	○	○	○
Australians need better access to health information and tools	○	○	○	○	○	○
Digital tools can help remove barriers to care in Australia, particularly for disadvantaged communities.	○	○	○	○	○	○
Health data should be used to make smarter decisions	○	○	○	○	○	○

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Pureprofile

95%

Which of the National Digital Health Strategy key outcomes mean the most to you?

Please drag and drop the options OR please click each option to rank

Digitally enabled
Health and wellbeing services are connected, safe and sustainable

Person-centred
Australians are empowered to look after their health and wellbeing, equipped with the right information and tools

Inclusive
Australians have equitable access to health services when and where they need

Data-driven
Readily available data making at the individual, community and national levels, contributing to a sustainable health system.

Rank 1

Rank 2

Rank 3

Rank 4

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Pureprofile

97%

That is all the questions we have for you today.

If you want to provide any further comments about the questions or survey in general or the answers you provided, please do so below.

Please click "NEXT >" to submit your survey...

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Figure A7.3: Predicted best probabilities (grouped results)