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Systematic Review: Cost-Effectiveness Analysis of Artificial Intelligence in Cancer Management

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ABSTRACT

Cancer is a leading cause of death worldwide and is associated with significant global economic losses. In this context, several innovations are introduced in the treatments but cost-effectiveness remains controversial. Artificial intelligence (AI) has massively assisted in the diagnosis, prognosis, and determination of cancer management. Therefore, this research aimed to systematically review the implementation of AI and cost-effectiveness in cancer treatment. The analysis followed PRISMA guidelines and used the PubMed database. The search strategy was conducted up to 2 September 2023 using three main keywords, namely "Cost-effectiveness analysis", "Cancer", and "Artificial intelligence". From 1746 retrieved articles, a total of 11 were included in the analysis. The results showed that there were two types of AI interventions in cancer, namely screening (n = 6; 55%) and surgery (n = 5; 45%). Meanwhile, prostate cancer was the most frequently analyzed (n = 3; 27%). Cost-effectiveness analysis reported that the implementation of AI was cost-effective (n=5, 46%), particularly in cancer screening intervention. AI intervention in screening was the most cost-effective strategy. In contrast, AI implementation in surgery showed inconsistent results, with limited research addressing the economic evaluation.

Keywords: Cost-effectiveness analysis, Cancer, Artificial intelligence, Systematic review

INTRODUCTION

Cancer is among the leading causes of death on a global scale (World Health Organization, 2022). In 2020, the global incidence reached 19.3 million with 10 million deaths, equivalent to 1 in 6 deaths. (Sung et al., 2021; World Health Organization, 2022). Additionally, the global economic loss due to cancer from 2020 to 2050 will be $25.2 trillion (at constant 2017 prices), equivalent to an annual tax of 0.55% on the global gross domestic product (GDP) (Chen et al., 2023). In this context, effective strategies are needed to reduce the mortality rate and the economic burden caused by cancer. For decades, several innovations were introduced from cancer screening; using big data and computational methodologies, to therapy; such as immunotherapy and stem cell-based therapy with controversial cost-effectiveness (Debela et al., 2021; Elmore et al., 2021). The advancements in digital technology, such as the Internet of Things (IoT), Artificial Intelligence (AI), Augmented Reality (AR)/Virtual Reality (VR), and cloud computing also assist in the diagnosis, prognosis, and determination of the most effective therapy for patients (Aikemu et al., 2021; Burati et al., 2022; Chassagnon et al., 2023; Hamabe et al., 2022; Iqbal et al., 2021; Juwara et al., 2020; Kaul et al., 2023; Li et al., 2023; Majumder & Sen, 2021; Pantanowitz et al., 2020; Zhang et al., 2022).

AI possesses cognitive abilities similar to humans to tackle complex healthcare challenges, such as cancer, by using data-based algorithms and programs enabled early and precise diagnosis and prediction (Huang et al., 2023; Sebastian & Peter, 2022). Currently, several research explored the application of AI in treatment, including lung and urology cancer screening, decision-support tools for colorectal cancer treatment strategies, and the creation of three-dimensional models for preoperative simulation of rectal cancer (Aikemu et al., 2021; Chassagnon et al., 2023; Hamabe et al., 2022; Pak et al., 2024). AI can predict the presence of lung cancer using deep learning technology by analyzing clinical data and imaging results from CT scans (Chassagnon et al., 2023). The utilization of AI in personalized medicine for colorectal cancer treatment has also shown that recommendations from supporting systems can match the accuracy of expert teams in determining the appropriate therapy based on patient age, cancer stage, and therapy history (Aikemu et al., 2021). In the organ simulation field, AI technology has been developed to automatically create three-dimensional models from MRI scans of the pelvis for preoperative simulation of advanced-stage rectal cancer.This technology can deliver results in 133 seconds with a general success rate of 100% (Hamabe et al., 2022).

In the United States, the utilization of AI in healthcare services is estimated to reduce expenditures by up to $150 billion in 2026 (Väänänen et al., 2021). The private sector has the potential to save about 7% to 9% of the expenditures, equivalent to annual savings of $80 billion to $110 billion over the next five years. Meanwhile, healthcare providers could reduce operational costs by 3% to 8%, translating to savings between $20 billion and $60 billion over the next five years. The use of AI technology reduces inefficiencies and maximizes the return on investment (ROI) in healthcare services (Alnasser, 2023). For example, AI application in screening colonoscopy is a cost-saving strategy to further prevent colorectal cancer incidence and mortality (Areia et al., 2022).

Most current publications primarily report on the accuracy and precision of AI advancements (Gore, 2020). A limited number of supportive health economic evaluations contributes to insufficient regulatory policies before its widespread implementation (Spadaccini et al., 2024; Wiegand et al., 2020). Healthcare professionals are overwhelmed by the enormous AI innovations in determining the criteria for clinical adoption (Voets et al., 2022). Therefore, a systematic literature review is conducted on cost-effectiveness of AI applications in cancer treatment. This research aids policymakers on AI policies and regulations in cancer treatment, as well as provides information to healthcare providers and patients about the implementation of AI technology.

MATERIALS AND METHODS

Research protocol

This review follows the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocols (Page et al., 2021). The literature search process included all peer-reviewed articles published on PubMed before September 2, 2023. Furthermore, the search on the PubMed database was conducted using Medical Subject Headings (MeSH) from three keywords: “Cost-effectiveness analysis”, “Cancer”, and “Artificial intelligence”. A complete search term was included in the supplement.

Eligibility criteria

The population targeted was cancer patients with AI intervention. The inclusion criteria were articles that discussed cost-effectiveness analysis of using AI in cancer treatment, original research articles, as well as articles written in English, and accessible. Selected articles must include cost-effectiveness analysis and the incremental cost-effectiveness ratio (ICER) values.

The articles were excluded after meeting the criteria of not addressing full cost-effectiveness analysis, failure to include AI intervention in cancer treatment, review articles, only abstract or poster articles, the full text not being written in English, and articles reflected as letters or editorials.

Research selection

From the PubMed database, retrieved citations were saved to the Mendeley reference manager for duplication identification. Subsequently, title abstract eligibility extraction was independently reviewed based on eligibility criteria by AAM and EUU. The disagreement was resolved by consensus with AM and MNBM. Meanwhile, the final full text was reviewed independently by AAM, AM, and MNBM. The systematic review process was presented in a flowchart according to the PRISMA method (Figure 1).

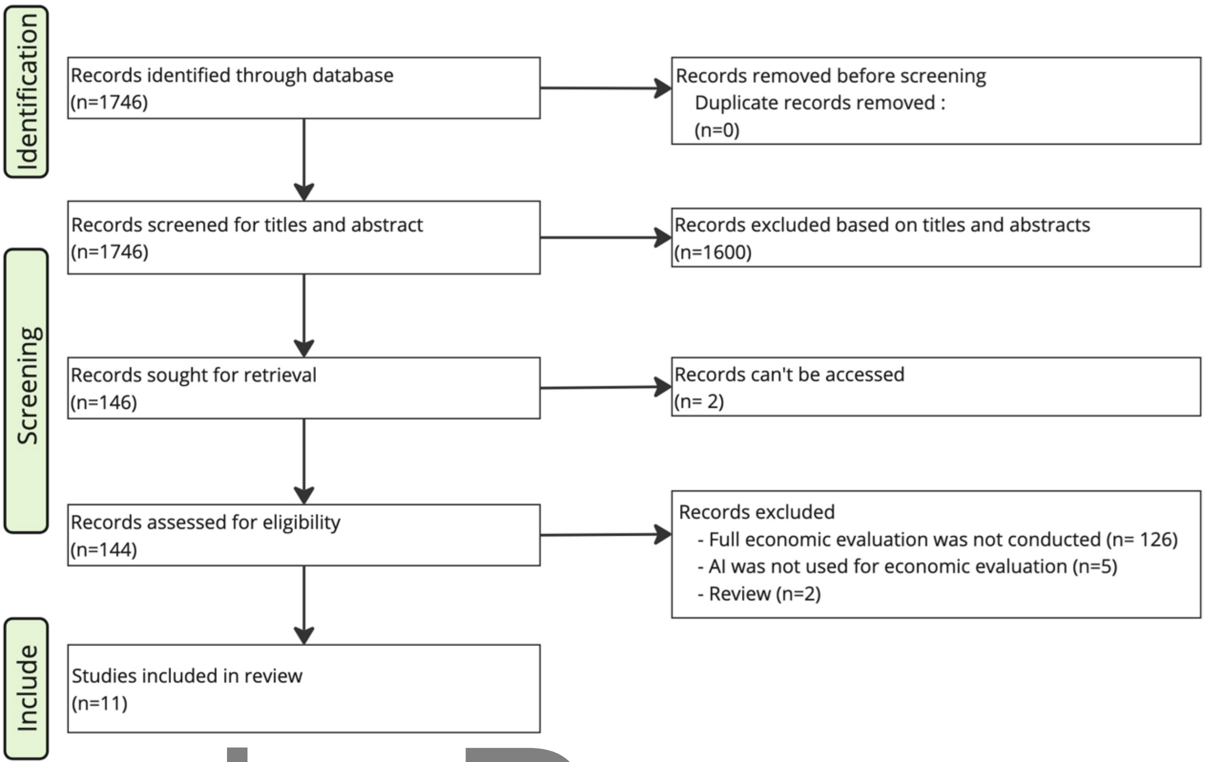

Figure 1. PRISMA diagram of this review

Table I. Characteristics of included research

Category	n=11(%)	Category	n=11(%)
Country		**Perspective**	
United States	5 (45.5)	Healthcare	5 (41.7)
Netherland	3 (27.3)	Third Payer	3 (25.0)
Denmark	1 (9.1)	Societal	3 (25.0)
Canada	1 (9.1)	Not mentioned	1 (8.3)
United Kingdom	1 (9.1)		
Types of Cancer		**Research Design**	
Prostate	3 (27.3)	Modelling research	
Bladder	2 (8.2)	Markov research	4 (36.4)
Cervical	2 (18.2)	Decision tree	2 (18.2)
Skin	2 (18.2)	Other modelling research	1 (9.1)
Breast	1 (9.1)	Trial based research	
Colorectal	1 (9.1)	Retrospective research	2 (18.2)
Types of Intervention		Prospective research	1 (9.1)
Cancer screening	6 (54.6)	Clinical trial	1 (9.1)
Cancer surgery	5 (45.5)		

Data collection process and data item

Data are collected for each article deemed eligible for extraction, including the population and country of the research, design, type of cancer, type of intervention, health economic perspective, comparators, intervention modality, ICER values, and conclusion for each article (Table I). In addition, data extraction was conducted by AAM and verified by AM and MNBM.

RESULTS AND DISCUSSION

The results showed that the AI interventions in cancer management were mainly in two areas, namely screening and surgery.

Research selection

The initial literature search generated 1,746 articles. After titles and abstracts were screened in line with the criteria, 1,600 articles were excluded. The screening for accessibility led to the exclusion of 2 more articles, resulting in 144. The eligibility assessment of the 144 articles was conducted based on full-text eligibility criteria, resulting in the exclusion of 133. In this context, 126 articles focused solely on cost and effectiveness comparisons, 4 articles did not use AI for economic evaluation, and 2 were review research. According to the PRISMA guidelines for literature selection, 11 articles were included.

Setting and design of the included research

The majority of the 11 research that met the eligibility criteria for data extraction were conducted in the United States (n = 5; 45.5%). The results show that the United States has the largest number of research on the application of AI in cancer management (Wang et al., 2023).

This research reported prostate cancer as the most frequent type analyzed in the AI application (n = 3; 27.3%). Prostate cancer is very common among men in Western countries (Kimura, 2012). Therefore, most of the research are carried out in the United States and Netherlands (Table I). In The United States and the Caribbean, the highest incidence of prostate cancer is among black men (American Society of Clinical Oncology, 2023).

Based on the results, the majority of AI interventions in cancer management can be divided into screening (n = 6; 54.6%) and surgery (n = 5; 45.5%). In real-world opportunistic screening, AI demonstrates strong potential for large-scale screening, offering a feasible and effective approach for early detection cases that health-professional initially missed which may improve workflow (Cabral et al., 2023; Hu et al., 2025a; Jassim et al., 2025). Additionally, in cancer surgery, AI-enhanced robotic surgery had increased to 15% per year as it could increase surgeon workflow efficiency and save in healthcare costs over the conventional procedures which lead to surgical outcomes (Jassim et al., 2025; Mehta et al., 2022). Although its benefit, challenges such as cost, ethical considerations, and the need for rigorous training protocols on more safety corncerns surgery, such as in pediatric and neurosurgical oncology, could hinder its widespread adoption (Wah, 2025).

Most of the research used a healthcare perspective in cost-effectiveness analysis (n = 5; 41.7%). The healthcare perspective focuses on costs and outcomes directly related to the collection of data, conduction of evaluations, and reduction of uncertainty (Sittimart et al., 2024). Some guidelines have recommended the societal perspective as the most appropriate for efficient resource allocation in society. However, this recommendation has drawbacks due to the uncertainty of cost components such as lost productivity (Kim et al., 2022).

Besides healthcare perspective, modeling research was adopted (n=7, 64%) due to the flexibility of applying a systematic analysis of long-term outcomes, costs, and impacts of various interventions (Xie et al., 2023). In addition, modeling can simulate patient pathways, disease progression, and treatment effects over time. There is also a higher risk of bias compared to trial-based research since simplified assumptions affect the results (Frampton et al., 2022). Health economics of AI implementation studies found inconsistent reporting quality such as AI cost components, learning-over-time modeling, and the barriers implementation would interfere the reliable recomendationfor healthcare decision making (Zhang et al., 2025).

Markov model was the most common design applied in modeling research (4, 36.4%). Compared to decision tree and DES, Markov (cohort simulation) and microsimulation approaches offer clear structures and high computational efficiency (Jayasekera & Mandelblatt, 2020; Ramos et al., 2023). This mathematical modeling simulates the progression of health conditions to evaluate and compare costs and outcomes of various interventions (Komorowski & Raffa, 2016). Markov research is most commonly applied in new healthcare interventions within the hypothesis stage. This includes the application of AI in cancer management due to the comprehensive interventions in simulating model time-dependent changes between different health states, handling uncertainty, and simulating patient pathways without requiring large sample sizes or long-term trials (Carta & Conversano, 2020).

AI implementation in cancer treatment

AI implementation was applied in cancer screening and surgery in eleven research. Cervical, skin, breast, and colorectal cancers were addressed in six research using AI for cancer screening. AI applications in surgical procedures were limited to prostate and bladder cancer.

AI implementation in cancer screening

In cervical cancer screening, AI implementation was evaluated in two research. The first research explored the application of the technology as a screening method using a neural network for pattern identification. This method is called PAPNET and can be used to reduce the false-negative error rate for squamous intraepithelial lesions (SIL) by 25% and a high SIL of 15%. Therefore, PAPNET reduces the cumulative lifetime incidence of invasive cancer by 40%. The end-impact decreases cervical cancer morbidity and mortality to save lives. PAPNET is also cost-effective compared to other widely practiced healthcare interventions (Schechter, 1996). The second research was the development of Interactive Neural Network-Assisted (INNA) screening for cervical cancer. The implementation of INNA can identify undetected cases of cervical epithelial abnormalities and potential cancer (Radensky & Mango, 1998).

For skin cancer screening, AI has shown potential evidence in two research. The first research investigated the use of AI for diagnostic support systems in assisting the detection and assessment of melanoma lesions in skin photography. The results showed that AI application had a comparable performance to standard care practices on QALY with less costs (Gomez et al., 2022). The second research was the development of an AI-powered mHealth app known as SkinVision to classify the risk level of skin cancer. The implementation of SkinVision led to a 32% increase in the identification of premalignant skin lesions. Additionally, users reported a higher rate of benign lesion claims compared to standard detection methods (Smak et al., 2023).

In breast cancer screening, AI was designed to stratify risk, comparing the effectiveness of early screening methods based on family history, the United States Preventive Services Task Force (USPSTF) screening guidelines, the American College of Obstetricians and Gynecologists (ACOG)/American College of Radiology (ACR) guidelines, and the absence of a screening strategy. The application of AI can accurately identify, and screen more high-risk women (Mital & Nguyen, 2022). For colorectal cancer screening, a simulated Computer-Aided Detection (CAD)-assisted colonoscopy showed fewer lifetime colorectal cancer cases and death by 30.4% and 32.7%, as well as a total cost savings of $143 per person (Thiruvengadam et al., 2023). AI assisted screening would improve lesion detection, characterization, and quality assurance during colonoscopy (Spadaccini et al., 2024).

AI assisted would benefit the early detection in cancer that lead to slow cancer progression, lowering cancer mortality and improving quality of life (Hu et al., 2025b; D. H. Kim et al., 2022; Mon et al., 2024). Even in in strict resources scenarios where decision-makers hesitate to allocate, a risk-stratified screening was likely to be cost-effective, yielding added health benefits at reduced costs (Hill et al., 2024).

AI implementation in cancer surgery

A total of three research investigated the application of AI in prostate cancer surgery. The first research evaluated the comparison of the application of Robot-Assisted Laparoscopic Prostatectomy (RALP) and Retropubic Radical Prostatectomy (RRP). Based on the result, the success rate of surgery using RALP was higher than RRP, with a difference of 7% (Hohwü et al., 2011). Meanwhile, the second research investigated the AI application for Stereotactic Body Radiotherapy (SBRT), or Cyberknife®, compared to standard treatment (fixed gantry SBRT). Cyberknife® can correct misalignments during the setup and treatment delivery process (Sharieff et al., 2016). The third research compared Robot-Assisted Radical Prostatectomy (RARP) and Laparoscopic Radical Prostatectomy (LRP). The procedure time and length of hospital stay for RARP were shorter than for LRP (Lindenberg et al., 2022). Additionally, impact of AI-assisted in prostate MRI reading demonstrated an improve performance radiologic diagnosis for nonexpert readers (Nakrour et al., 2025; Twilt et al., 2025).

In bladder cancer surgery, a total of two research applied AI. The first research reported that Robot-Assisted Radical Cystectomy (RARC) showed similar effectiveness to Open Radical Cystectomy (ORC) in reducing complications. The difference in the proportion of patients experiencing complications within 1 year was minimal, with 67% and 64% for ORC and RARC, respectively (Michels et al., 2022). The second research showed that Intracorporeal Robot-Assisted Radical Cystectomy (iRARC) was more effective in reducing short-term morbidity compared to ORC (Dixon et al., 2023). In addition, the robot-assisted approach offered less blood loss, shorter hospital stays, and fewer blood clots in bladder cancer (Khetrapal et al., 2023).

Cost-effectiveness analysis of AI in cancer treatment

Cost-effectiveness analysis of eleven research on economic evaluation was described explicitly. Meanwhile, a total of four research showed that the analysis could not be concluded due to the lack of WTP threshold. A total of 4 and 1 research evaluated the application of AI in cancer screening and surgery, respectively. The application of AI in screening was cost-effective in breast, cervical, skin, and colorectal cancer. In surgery, AI application in prostate cancer showed cost-effective strategy.

Even though the implementation of AI required an additional cost of $97.6 million compared to no screening in breast cancer, the additional benefit value was 4,110 QALYs, resulting in an ICER of $23,755 below the WTP threshold of $100,000 (Mital & Nguyen, 2022). Despite its high costs, combination of mammography and breast MRI offers the most effective detection method (Covington, 2025). Implementation of AI-assisted MRI reading in breast cancer screening can reduce the number of missed cancers ((Quality), 2023; Salim et al., 2024). Due to qualified MRI staff are lacking, AI-assisted screening was beneficial showed nearly four times more efficient in terms of cancers detected per 1,000 MRI examinations making the cost per cancer detected comparable with screening mammography (Salim et al., 2024). This strategy is more beneficial for early detection in women with intermediate risk in lowering the screen reading workload burden and costs, while maintaining a high cancer detection without increasing false positives. (Hernström et al., 2025; van Winkel et al., 2025).

The AI application also cost-effective for rescreening cervical cancer compared to various manual methods reported an ICER ranging from $35,000 to $80,000 per life year saved (LYs) with a WTP threshold of $100,000 (Radensky & Mango, 1998). AI was predicted as a new, rapid, low-cost, HPV testing can allow for high-volume screening by enabling interpreted high resolution digital colposcopy images for lesions detection thus can be treated easily and effectively (Bedell et al., 2020). Moreover, screening in more high-risk patients would be more effective and cost-effective as alternatives for the current triage strategy to reduce the unnecessary referrals (Jansen et al., 2021). Early detection also improved the 5-year survival rate of women diagnosed with invasive cervical cancer compared to advanced or metastatic state (Mahajan et al., 2024; Sung et al., 2021).

The benefit of QALY value of AI for skin cancer screening was similar andcosts were lower compared to comparators, with an average of $750 vs $759 (Gomez et al., 2022). The CAD for colonoscopy in colorectal cancer screening showed less costs of $143 with an incremental benefit of 0.01 QALY (Thiruvengadam et al., 2023). AI benefitted medical professionals by improving the overall sensitivity and specificity for skin cancer detection with the the benefit is more pronounced in non-dermatologists (Krakowski et al., 2024; Salinas et al., 2024).

In surgery application, RARP and LRP for prostate cancer surgery cost €12,078 and €10,049, with QALYs of 6,17 and 6,11, respectively. RARP in prostate cancer surgery was considered cost-effective based on long-term impact and when performed by experienced surgeons using robotic surgical tools (Lindenberg et al., 2022). Robot-assisted laparoscopic radical prostatectomy was shown to have better outcome in term of positive apical margin which strongly associated with biochemical recurrence free survival (Yu et al., 2018). In recent study, the implementation of RARP in combination with NeuroSAFE, a standardised frozen section analysis to guide nerve-sparing, not only improves postoperative erectile function and early urinary continence recovery but also increasing the chance of successful nerve preservation (Dinneen et al., 2025).

A total of two research were not cost-effective and the first investigated the application of RARC for bladder cancer surgery with the ORC as a comparator. RARC had a higher cost with almost similar benefits compared to ORC. From the healthcare perspective, RARC and ORC had an average cost of €21,266 and €17,141 with benefit values of 0.79 QALY and 0.81 QALY, respectively. Therefore, RARC is not considered cost-effective compared to ORC in the management of bladder cancer surgery (Michels et al., 2022). After 1 year, the two approaches were also similarly in QALYs but is more expensive, which show that RARC does not seem to provide value for money in comparison to ORC (Joyce et al., 2023).

Table II. Detailed extraction of included research

Ref	Population (Country)	Research Design	Types of Cancer	Types of Intervention	Perspectives	Comparator	Intervention Modality	ICER	Conclusion
(Mital & Nguyen, 2022)	100,000 White Women (aged 40-49, United States)	*Hybrid decision tree/microsimulation model*	Breast Cancer	Cancer Screening	Healthcare perspective	Early screening is based on family history (similar to USPSTF guidelines), annual screening (similar to ACOG/ACR guidelines), and no screening.	AI is used for risk stratification based on the mammogram index	The ICER value is $23,755 per QALY with a WTP threshold of $100,000.	• Only the "no screening" strategy compared to the AI for low-risk women falls on cost-effectiveness efficiency frontier. • Higher accuracy of AI in identifying high-risk women compared to family history and PRS. • In this research, the use of AI can accurately identify, and screen more high-risk women, and avoid screening for low-risk women. This cost-effective AI-based screening strategy can help minimize delays in diagnosis as well as false-positive diagnoses that can arise with conventional screening strategies.
(Hohwü et al., 2011)	231 men (aged between 50 and 69 years, Denmark)	retrospective cohort research	Prostate cancer	Cancer surgery	Societal perspective	Retropubic radical prostatectomy (RRP)	Robot-assisted laparoscopic prostatectomy (RALP). RALP is a technology that can be an alternative to RRP due to its better outcomes. RALP was introduced in 2005 using the da Vinci system.	The ICER for direct costs is €64,343 per additional successful treatment using RALP. The QALY value could not be determined due to a lack of data.	• The success rate of surgery using RALP is higher than RRP, with a difference of 7%. • More RRP patients report post-operative erectile function compared to RALP. • Erectile medication prescriptions are more commonly used for RALP patients. • Long-term follow-up of outcome measurements and sick leave is needed to intensify cost-effectiveness assessment between these alternatives.
(Sharieff et al., 2016)	5,000 adult male patients with low risk of prostate cancer aged 70 ± 10 years (Canada)	Modelling research	Prostate cancer	Cancer surgery	Payer perspective	Arc-based dan Fixed-gantry Stereotactic Body Radiotherapy (SBRT)	Cyberknife®, a robotic SBRT device that can correct any misalignments during setup and treatment delivery.	$-2.497 / QALY ($-2.846, $-622), compared to the standard intervention (fixed gantry SBRT)	• Robotic SBRT is more cost-effective than standard regimens under moderate to high surgical volume conditions (6-10 hours of surgery per day). • Robotic SBRT appears to be more cost-effective than Arc-based and Fixed-gantry SBRT systems when considering cost per cure and cost per QALY, due to higher rates of biochemical evidence of disease (bNED). • Arc-based SBRT is the most cost-effective system in providing equivalent benefits.
(Lindenberg et al., 2022)	1,370 patients from 12 hospitals (Netherlands)	Decision tree	Prostate cancer	Cancer surgery	Societal perspective	Laparoscopic Radical prostatectomy (LRP)	Robot-Assisted Radical Prostatectomy (RARP)	RARP is more cost-effective with an ICUR of €34,206 below the WTP threshold of €80,000	• OR, personnel and hospitalization costs are lower for RARP due to shorter procedure time and length of stay. • RARP is more cost-effective compared to LRP when evaluating the long-term health and economic impact at the most acceptable WTP ratio. • RARP becomes cost-effective at all WTP ratios to save costs when centralized and experienced surgeons possess Da Vinci robots.

Table II. Detailed extraction of included research

Ref	Population (Country)	Research Design	Types of Cancer	Types of Intervention	Perspectives	Comparator	Intervention Modality	ICER	Conclusion
(Smak et al., 2023)	General population (aged 18 years and above, Netherlands)	Retrospective cross-sectional research	Skin cancer	Cancer screening	Not stated	Dermatologists in primary, secondary, and tertiary care	An AI-based mHealth app with CNN algorithm (SkinVision) to classify skin lesion cancer risk based on images	€2,567 per additional detected (pre)malignant skin lesion	• The use of mHealth applications can increase claims for (pre)malignant skin lesions by 32%. • mHealth users report higher claim rates for benign lesions. • Further improvements in the diagnostic accuracy of algorithms and a more targeted method for high-risk populations or high-risk lesions appear to be important steps forward for the successful and cost-effective implementation of mHealth applications for skin cancer diagnosis.
(Michels et al., 2022)	348 bladder cancer patients (aged 18 years and above, Netherlands)	Prospective multicentre comparative-effectiveness research	Bladder cancer	Cancer surgery	Healthcare perspective & Societal perspective	Open radical cystectomy (ORC)	Robot-assisted radical cystectomy (RARC).	RARC cost-effectiveness value of 0.6% (healthcare perspective) and 0.2% (societal perspective) using a WTP threshold of €80,000 per QALY.	• Implementation of RARC is more expensive than ORC. The QALY value of RARC is also not much different from ORC. • According to the research results, the QALY values of 0.79 (RARC) and 0.81 (ORC) are not different. The implementation of RARC requires additional costs of €112,125 and €162,253 from healthcare and societal perspectives, respectively. • RARC is considered not cost-effective to implement.
(Dixon et al., 2023)	305 adults with non-metastatic bladder cancer, squamous, adenocarcinoma, or variant (United Kingdom)	Multicenter, unblinded, randomized clinical trial	Bladder cancer	Cancer surgery	Healthcare perspective	Open radical cystectomy (ORC)	Robot-assisted radical cystectomy with intracorporeal urinary diversion (iRARC)	The ICER value from iRARC is £100,008 with a WTP threshold of £20,000/ QALY.	• iRARC is more effective in reducing short-term morbidity compared to ORC for bladder cancer patients. • iRARC has several advantages, including reduced length of hospital stay, ICU admissions, and readmissions. • Cost of implementing iRARC is higher than ORC, resulting in an ICER value above the normal threshold in the UK. • Sensitivity analysis suggests that iRARC could be more cost-effective considering several options. First, reducing robotic surgery time has a significant impact on cost-effectiveness. Second, more general changes in healthcare service cost levels (excluding equipment prices) have a relatively small effect due to the offsetting effects of iRARC, which results in higher operating theater costs but lower ward costs.
(Schechter, 1996)	100,000 women screened every 2 years (ages 20-64, United States)	Markov model	Cervical cancer	Cancer screening	Healthcare perspective	Standard intervention	PAPNET testing, cancer screening method using neural network technology, is a branch of AI well-suited for pattern identification.	Assuming a low false-negative error rate for squamous intraepithelial lesion (SIL) of 25% and a high SIL of 15%, and applying a 30% increase in sensitivity from PAPNET,	• Key findings of this research are that PAPNET testing can reduce cervical cancer morbidity and mortality and save lives more cost-effectively than other widely practiced healthcare interventions. • PAPNET can reduce the cumulative lifetime incidence of invasive cancer by 40%.

Table II. Detailed extraction of included research

Ref	Population (Country)	Research Design	Types of Cancer	Types of Intervention	Perspectives	Comparator	Intervention Modality	ICER	Conclusion
(Gomez Rossi et al., 2022)	1000 random individuals (aged 12-50 years, United States)	Markov Model	Skin cancer	Cancer screening	Payer perspective	Standard care	AI was developed as a diagnostic support system to assist in the detection and/or assessment of melanoma lesions in skin photography.	- $27,580/QALY. The acceptability curve shows that adopting this technology is more likely to be cost-effective at lower WTPs; progressively increasing WTPs	• QALY values are not significantly different from standard care • The ICER value of AI implementation suggests that AI tends to be more cost-effective at a lower WTP threshold, showing sensitivity to high WTP. • Univariate sensitivity analysis of cost paid for AI use shows that AI becomes the dominant strategy when service costs exceed $16.
(Radensky & Mango, 1998)	100,000 women (aged 25-75 years, United States)	Markov Model	Cervical cancer	Cancer rescreening	Payer perspective	Manual screening	Interactive neural network–assisted (INNA) screening	The ICER value from the primary analysis (assuming a sensitivity of 85% for traditional manual screening), is around $35,000 to $80,000 per QALYs with a threshold value of $100,000.	• Findings from this research suggest that the use of INNA for cervical cancer rescreening has the potential to be more cost-effective. • The implementation of INNA can identify undetected cases of cervical epithelial abnormalities and potential cervical cancer. • Cost-effectiveness of INNA falls well below the $100,000 per LY saved threshold.
(Thiruvengadam et al., 2023)	10,000 patients (United States)	Semi-Markov microsimulation model	Colorectal cancer	Cancer screening	Healthcare perspective	Traditional colonoscopy	Colonoscopy aided by computer-aided detection (CAD) technology	Real-time CAD-assisted colonoscopy emerges as the dominant strategy due to its superior effectiveness and lower cost, resulting in a $143 cost reduction and an additional 0.01 QALY gain. This technology establishes itself as the dominant and cost-effective strategy under a WTP threshold of $100,000/QALY.	• CAD is the dominant strategy, resulting in 30.4% fewer lifetime colorectal cancer cases, 32.7% fewer colorectal cancer deaths, and a total cost savings of $143 per person. • Although CAD increases national resources by increasing the total number of colonoscopies performed by 4.2 million, the overall reduction in colorectal cancer treatment costs results in cost savings of $4.7 billion.

The second research was the application of iRARC for bladder cancer surgery. iRARC was found to be more effective in reducing short-term morbidity compared to ORC for bladder cancer patients. However, the application requires an additional cost of £1,124 with a small difference in benefits of 0.01124 QALY. The ICER was £100,008/QALY above the normal WTP threshold in the UK (£20,000/QALY). The strategy was not cost-effective due to the increased cost of operating time and equipment in the application of iRARC (Dixon et al., 2023). Despite RARC showed comparable oncological outcomes and better post-operative QoL, RARC encompased learning curve to overcome lead to future research recomendation in large-scale patients (Han & Ku, 2023).

A total of four research did not present cost-effectiveness analysis as monetary per QALY, creating challenges in comparing the result with WTP threshold. The first research stated that the application of RALP for prostate cancer surgery required twice cost of RRP. The ICER value is €64,343 per additional successful treatment, which is considered not cost-effective due to higher cost and minimal difference in effectiveness compared to RRP (Hohwü et al., 2011). The second research compared Robotic Stereotactic Body Radiation Therapy (SBRT) using "Cyberknife®" with standard regiment (fixed gantry SBRT) and ICER of $-2.497/QALYs (Sharieff et al., 2016). The third research stated that the application of PAPNET testing had an ICER value for biennial and triennial screenings of $48,474/LY and $25,185/LY, respectively (Schechter, 1996). In the fourth research, SkinVision users had a higher average annual healthcare cost of €64.97 compared to €43.09 per person. The biggest differences in costs were for nevi consultations (€11.05 per person vs €2.71, $p < 0.001$) and premalignant or malignant skin neoplasia (€31.01 per person vs €20.88, $p < 0.001$). This research reported an ICER of €2,567 per additional premalignant skin lesion detected (Smak et al., 2023).

WTP is a tool to asses a technology for decision making process. It is generally considered good value for money when the ICER is below a certain implicit or explicit WTP threshold (Schurer et al., 2022). However, WTP was varied across different circumtances. Developed countries have WTP thresholds with established health technology assessment systems. For example, the United Kingdom possessed WTP threshold of £20,000/QALY for bladder cancer surgery (Dixon et al., 2023; Vu et al., 2024). Meanwhile, developing countries may not have WTP threshold due to limited resources, lack of infrastructure, and other urgent health and economic challenges (Vu et al., 2024). The WHO recommends a WTP threshold of three times the GDP of a country for the intervention to be considered cost-effective when the ICER value is reduced (World Health Organization, 2003). Additionally, WTP was adjusted to severity of illness and permanent diasability (Phelps & Lakdawalla, 2023). In some cases, WTP is higher in the more higher disease severity and the more younger age population impact (Reckers-Droog et al., 2021).

This research shows several challenges in cancer management using AI application. First, AI implementation in surgery mostly needs a large investment in equipment compared to the screening strategy. The investment in AI-based surgery can be fairly adjusted when the modeling research incorporates more long-term benefits with an increased population. Second, cost-effectiveness analysis was mainly focused on the unit effectiveness, such as extra successful treatment, additional cases prevented, and life years gained. In AI application, dollars allocated to technology investment increase the health impact and optimize professional resources.

Limitation

This research analyses cost-effectiveness of AI application in cancer management. Concerning the limitations, some eligible research were excluded since only the PubMed database was used. The search strategy also retrieved the potential article from the bibliography of the included research to minimize the level of undetection.

The majority of the extracted research excluded similar ICER values as monetary per QALYs. The willingness-to-pay data were not provided and this research was recommended as cost-effective for the AI application. The incorporated modelling-based economic evaluation led to a higher risk of bias compared to trial-based research. However, modeling analyses are suitable for implementing AI development or evaluation in cancer management to test interventions in the hypothesis or trial stage.

CONCLUSION

In conclusion, AI interventions in cancer management were mainly in the areas of screening and surgery. Prostate cancer was the most commonly analyzed type for AI applications. Most research reported that AI-based cancer management strategies were cost-effective, particularly in cancer screening interventions.

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CONFLICT OF INTEREST

The authors reported no conflicts of interest.

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