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The application and use of artificial intelligence in cancer nursing: A systematic review

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A R T I C L E I N F O

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Artificial intelligence
Cancer nursing
Machine learning
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A B S T R A C T

Purpose: Artificial Intelligence is being applied in oncology to improve patient and service outcomes. Yet, there is a limited understanding of how these advanced computational techniques are employed in cancer nursing to inform clinical practice. This review aimed to identify and synthesise evidence on artificial intelligence in cancer nursing.

Methods: CINAHL, MEDLINE, PsycINFO, and PubMed were searched using key terms between January 2010 and December 2022. Titles, abstracts, and then full texts were screened against eligibility criteria, resulting in twenty studies being included. Critical appraisal was undertaken, and relevant data extracted and analysed. The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines were followed.

Results: Artificial intelligence was used in numerous areas including breast, colorectal, liver, and ovarian cancer care among others. Algorithms were trained and tested on primary and secondary datasets to build predictive models of health problems related to cancer. Studies reported this led to improvements in the accuracy of predicting health outcomes or identifying variables that improved outcome prediction. While nurses led most studies, few deployed an artificial intelligence based digital tool with cancer nurses in a real-world setting as studies largely focused on developing and validating predictive models.

Conclusion: Electronic cancer nursing datasets should be established to enable artificial intelligence techniques to be tested and if effective implemented in digital prediction and other AI-based tools. Cancer nurses need more education on machine learning and natural language processing, so they can lead and contribute to artificial intelligence developments in oncology.

1. Introduction

Over 19 million new cancer cases were reported and almost 10 million people died from cancer in 2020 (Sung et al., 2021), making it the leading cause of death worldwide. A number of risk factors can contribute to the development of cancerous cells including a poor diet, lack of exercise, smoking, alcohol intake, a persons' genetic makeup, along with various biological and environmental carcinogens. The diagnostic process often requires a comprehensive clinical evaluation by multidisciplinary teams of healthcare professionals, followed by a range of interventions that could include one or a combination of surgery, radiotherapy, and systemic anti-cancer therapy to treat the disease and help manage its symptoms. Hence, people diagnosed with cancer can experience a significant burden from the illness which impacts their physical, psychological, and social health (Erdoğan Yüce et al., 2021). Therefore, the World Health Organization (WHO) emphasise the importance of early detection (screening and diagnosis), appropriate treatment, and supportive care to help reduce the burden of cancer

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(WHO, 2022).

Oncology clinical nurse specialists or advanced nurse practitioners are key to supporting patients with the burden of cancer as they are involved in many aspects of the cancer pathway from assessing patients, to facilitating diagnostic procedures and treatments, and delivering personalised and holistic care in acute hospital settings. Nurses in the community also support patients and their families at different stages of the cancer pathway. Cancer nurses may use a range of technologies in their daily practice such as electronic health records (Caligtan and Dykes, 2011), telehealth for remote monitoring and consultation (Paterson et al., 2020), and mobile health applications (apps) (Magalhães et al., 2021) to name a few. They also support patients to use technologies such as online health services, social media, health apps, and wearable devices for self-management throughout their cancer journey (Cannon, 2018; Watson, 2018; Wilson and Mooney, 2020). More advanced analytics in the form of Artificial Intelligence (AI) techniques are being integrated into these digital tools to better support patient care and the delivery of cancer services.

AI comprises a suite of sophisticated computational techniques that are used to analyse and understand complex datasets, which is becoming more common in the field of oncology to enhance cancer care. Samoili et al. (2020) define AI as "*software (and possibly also hardware) systems designed by humans that, given a complex goal, act in the physical or digital dimension by perceiving their environment through data acquisition, interpreting the collected structured or unstructured data, reasoning on the knowledge, or processing the information, derived from this data and deciding the best action(s) to take to achieve the given goal. AI systems can either use symbolic rules or learn a numeric model, and they can also adapt their behaviour by analysing how the environment is affected by their previous actions*". It encompasses a range of techniques grouped into machine learning (supervised, unsupervised and reinforcement learning), natural language processing (NLP), and fuzzy logic, with more domains within the AI field currently being explored.

AI has been used in oncology to identify risk factors associated with different types of cancers (Bi et al., 2019), to help predict mortality and disease reoccurrence (Palazón-Bru et al., 2019), and to facilitate genomic cancer profiling (Xu et al., 2019). Deep learning is one very popular AI technique, where artificial neural networks a type of supervised machine learning, are employed to analyse complex data such as medical images which can be used to improve cancer diagnosis (Murtaza et al., 2020). A number of systematic and scoping reviews of AI in the nursing and midwifery professions have been published recently (O'Connor et al., 2023; Seibert et al., 2021; von Gerich et al., 2022) but few included studies were related to oncology. As cancer has unique populations of patients and a multitude of different illnesses, diagnostic procedures, treatments, and disease trajectories, it is important to understand how AI is being employed in cancer nursing. This could support understanding how AI techniques can be applied across different areas of cancer nursing, identifying knowledge gaps that need addressing to enhance patient care and professional practice, and recommending changes needed in cancer nursing education, clinical practice, research, and policy. Hence, this systematic review aimed to:

1) examine the areas of cancer nursing AI has been applied in,
2) determine how involved cancer nurses were in AI research, and
3) understand the limitations and risks of AI in cancer nursing.

2. Methods

2.1. Search and screening strategy

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) checklist guided the conduct of the review (Page et al., 2021). Bibliographic biomedical databases i.e., CINAHL (EBSCOhost), MEDLINE (Ovid), PubMed (Central), and PsycINFO (Ovid) were searched between January 2010 and December 2022. Terms related to cancer, nursing, and AI were searched for example: "((cancer*) AND (nurs*) AND ("artificial intelligen*)) (Supporting File 1). Relevant MeSH terms and subject headings were added where appropriate. In addition, the top five cancer nursing journals as ranked by the 2021 impact factor (i.e., Seminars in Oncology Nursing, Cancer Nursing, European Journal of Oncology Nursing, European Journal of Cancer Care, and Asia-Pacific Journal of Oncology Nursing) were electronically searched using a subset of key terms. The eligibility criteria were developed in line with the Population, Exposure, Outcomes, and Study Design (PEOS) framework to help assess the relevancy of studies for inclusion in the review. The population were qualified nurses (excluding students) working in any area of oncology, exposure were studies where one or more AI techniques were applied to cancer data, outcomes were open-ended to capture the breadth of AI research in the field, and all types of study designs were included. Exclusion criteria were AI techniques or AI-based tools that were simulated, prototyped, or not applied to real cancer datasets or settings. Only peer-reviewed, primary studies or those undertaking secondary analysis, published in English language journals were included. Conference proceeding, discussion articles, grey literature, any type of literature review and theses were excluded.

A total of 586 articles were found through database and journal searching and the results uploaded to Rayyan (https://www.rayyan.ai/) for screening. The titles, abstracts, and full texts were screened against eligibility criteria by independent reviewers and those not relevant were discarded. Any disagreements during screening were discussed among the research team to reach consensus (Fig. 1).

2.2. Data extraction, critical appraisal, and analysis

A data extraction template was created on Microsoft Excel to summarise each included study. The primary author exacted all key study characteristics which were checked by another member of the research team. Grove et al. (2017) hierarchy of research evidence was used to classify the study design of each included study. This comprises seven levels, with level I being the highest level of evidence and level VII being the lowest, and was utilised as a form of quality assessment to help determine the weight of evidence on AI in cancer nursing. Ten studies (50%) were graded as level VI (descriptive), while a further ten (50%) were deemed level IV (descriptive correlational), as no randomized controlled trials or systematic reviews with meta-analysis were identified meaning the overall weight of evidence was low to medium. The extracted data were then analysed using descriptive statistics and content analysis (Kyngäs et al., 2020).

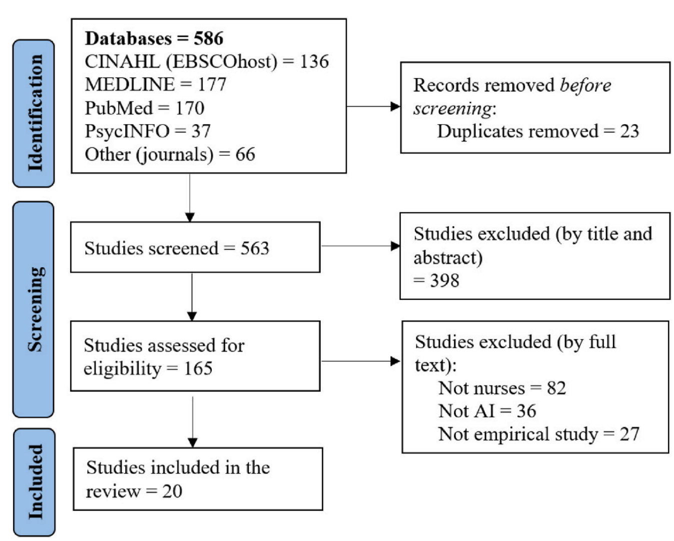

Fig. 1. Flow diagram of the screening process.

3. Results

3.1. Study characteristics

Twenty studies were included published between 2011 and 2022. Seven were conducted in China (Chen et al., 2021; Jin et al., 2022; Meng et al., 2022; Wei et al., 2021; Zeng et al., 2021; Wu et al., 2022), three in the United States of America (Im and Chee, 2011; Koleck et al., 2021; Lee et al., 2022), three in South Korea (Kim et al., 2019; Park et al., 2015; On et al., 2022), and one in Denmark (Olling et al., 2018), Finland (Vehviläinen-Julkunen et al., 2021), Iran (Soltani et al., 2022), Italy (Chiesa et al., 2021), Japan (Takehira et al., 2011), Switzerland (Günther et al., 2022), Taiwan (Chung et al., 2021), and The Netherlands (van de Sande et al., 2021).

The populations included patients with bladder, breast, dermatological, endocrine, gynaecological, haematological, head and neck, intestinal, liver, lung, neurological, ovarian, pancreatic, prostate, and testicular cancers, although several studies did not describe the specific disease groups (Table 1). Patients who typically were 50 years and older dominated, with only one study including paediatric participants (Chiesa et al., 2021). Most studies included a mix of male and female patients, although only a handful reported ethnicity (Jin et al., 2022; Wu et al., 2022; Im and Chee, 2011; Koleck et al., 2021; Vehviläinen-Julkunen et al., 2021). Most of the AI techniques involved some type of machine learning (Chen et al., 2021; Jin et al., 2022; Meng et al., 2022; Wei et al., 2021; Zeng et al., 2021; Kim et al., 2019; Park et al., 2015; On et al., 2022; Olling et al., 2018; Soltani et al., 2022; Chiesa et al., 2021; Takehira et al., 2011; Günther et al., 2022; van de Sande et al., 2021; Wu et al., 2022), and two studies focusing on fuzzy logic one of which incorporated NLP (Im and Chee, 2011; Chung et al., 2021). One study employed NLP (Koleck et al., 2021), and two used a combination of NLP and machine learning techniques (Lee et al., 2022; Vehviläinen-Julkunen et al., 2021).

The study designs used were largely quantitative in nature using observational, cross-sectional, case-control or other designs (Chen et al., 2021; Jin et al., 2022; Meng et al., 2022; Wei et al., 2021; Zeng et al., 2021; Im and Chee, 2011; Koleck et al., 2021; Lee et al., 2022; Kim et al., 2019; Park et al., 2015; On et al., 2022; Soltani et al., 2022; Chiesa et al., 2021; Takehira et al., 2011; Günther et al., 2022; Chung et al., 2021; van de Sande et al., 2021; Wu et al., 2022). Only two studies used mixed methods (Olling et al., 2018; Vehviläinen-Julkunen et al., 2021) and none adopted a qualitative approach. The settings in the included studies were mainly acute hospital environments where datasets from electronic medical records were utilised (Chen et al., 2021; Jin et al., 2022; Meng et al., 2022; Wei et al., 2021; Zeng et al., 2021; Kim et al., 2019; Park et al., 2015; On et al., 2022; Olling et al., 2018; Chiesa et al., 2021; Takehira et al., 2011; Günther et al., 2022; van de Sande et al., 2021; Wu et al., 2022), with one using a survey and focus groups with cancer patients conducted in a hospital (Vehviläinen-Julkunen et al., 2021), another was based at a cancer centre (Soltani et al., 2022), and another at a medical centre (Koleck et al., 2021). A single study used a dataset from a national health insurance database (Chung et al., 2021), while another used a dataset from an online cancer community forum (Lee et al., 2022), and one combined data from an Internet forum and a survey with cancer patients (Im and Chee, 2011) (Table 1).

3.2. AI in cancer nursing

AI has been used in numerous ways in cancer nursing (Table 1). Seventeen studies (85%) applied AI techniques to address clinical issues related to direct patient care including breast, colorectal, liver, and ovarian cancers, among others. They reported improvements in the accuracy of predicting health outcomes and in some cases identified variables that improved outcome prediction (Chen et al., 2021; Jin et al., 2022; Meng et al., 2022; Wei et al., 2021; Zeng et al., 2021; Im and Chee, 2011; Lee et al., 2022; Kim et al., 2019; Park et al., 2015; On et al., 2022; Olling et al., 2018; Vehviläinen-Julkunen et al., 2021; Chiesa et al., 2021; Takehira et al., 2011; Günther et al., 2022; van de Sande et al., 2021; Wu et al., 2022). In most of these studies, AI algorithms were trained and tested on primary or secondary health datasets to build predictive models of particular problems related to cancer. However, Wei et al. (2021) did deploy an AI model in a web-based application for general use, and only one study went further developing and implementing an AI-based decision support system with cancer nurses to evaluate its impact on clinical decision making and care delivery (Im and Chee, 2011). Although Koleck et al. (2021) had a clinical focus, it utilised NPL to identify symptoms and symptom clusters from EHR nursing notes as opposed to using AI algorithms to build a predictive model. Two studies (10%) focused on administration and management to help predict patient demand for oncology services (Soltani et al., 2022) and forecast cancer nursing manpower (Chung et al., 2021). None of the included studies centred on education or policy in cancer nursing.

3.3. Cancer nurses and AI research

Nurses led the application of the AI techniques and were the corresponding author in thirteen studies (65%) (Table 1) (Chen et al., 2021; Jin et al., 2022; Meng et al., 2022; Wei et al., 2021; Zeng et al., 2021; Im and Chee, 2011; Koleck et al., 2021; Lee et al., 2022; Kim et al., 2019; Park et al., 2015; On et al., 2022; Vehviläinen-Julkunen et al., 2021; Wu et al., 2022). Where nurses did not lead the research, the seven studies (35%) were led by colleagues from medicine, pharmacy, computer science, and health services research, demonstrating the interdisciplinary nature of oncology care. In these studies, nurses were actively involved by identifying eligible cancer patients for a study, undertaking clinical assessments or interviews as part of the data collection process, or analysing oncological patient data to identify clinical issues to compare to the outputs of a predictive model (Olling et al., 2018; Chiesa et al., 2021; Günther et al., 2022). In three studies (15%), nurses were passively involved by being a secondary source of patient or other cancer data used for analysis by AI algorithms (Chung et al., 2021; Soltani et al., 2022; Takehira et al., 2011). In one study (5%), cancer nurses were not involved but could be potential future users of the AI approach (van de Sande et al., 2021).

3.4. Limitations and risks of AI in cancer nursing

Several limitations related to AI in cancer nursing were reported. The main constraint was the quality of the health datasets used, as many were retrospective in nature, had small sample sizes, with variables missing or self-reported measures used, which might reduce the accuracy of the algorithms and predictive models. In addition, the data were often drawn from a single hospital which might limit the generalisability and usefulness of the AI approach in other settings (Chen et al., 2021; Jin et al., 2022; Meng et al., 2022; Wei et al., 2021; Zeng et al., 2021; Koleck et al., 2021; Kim et al., 2019; Park et al., 2015; On et al., 2022; Soltani et al., 2022; Takehira et al., 2011; Takehira et al., 2011; Chung et al., 2021; van de Sande et al., 2021). Lee et al. (2022) also warned of potential bias in existing health datasets as marginalised populations are likely to be underrepresented which could affect predictive algorithms. One study also noted a concern about the impact of AI-based digital tools on the workflow of clinicians (Olling et al., 2018). The authors suggested AI tools need to be integrated appropriately into clinical practice only after the predictive models undergo clinical validation, a point also raised in other studies (Wei et al., 2021; van de Sande et al., 2021). Furthermore, Meng et al. (2022) emphasised the lack of transparency in some machine learning methods can be challenging to understand the effects of the selected features on the final model. The authors recommended several machine learning techniques should be used to build a robust predictive model, a suggestion supported by others (Wei et al., 2021). Risks were rarely mentioned although privacy and regulatory issues related to AI were briefly noted in one study (van de Sande et al.,

Table 1
Characteristics of included studies.

Authors, Year, Country, Lead	Research aim(s) or objective (s)	Study design, Setting, Data collection	Participants	AI Intervention	Results/Outcomes
Authors: (Chen et al., 2021), Country: China, Lead: Nursing	To examine if machine learning can assist with recognising faces in distress	Study design: Not described; Setting: Hospital in Chengdu, China; Data collection: Distress Thermometer (DT) and Hospital Anxiety and Depression Scale (HADS), medical records, videos of patients' faces	Numbers: 232; Type: patients with cancer; Gender: 213 females and 19 males; Age: median age at first diagnosis of 48 years (range = 20–72 years); Ethnicity: primarily Chinese	Support vector machine (SVM), Viola–Jones algorithm, Histogram of oriented gradient descriptor (HOG)	Significant diagnostic value of using machine learning to recognise distress in patients with cancer. This approach could guide the assessment and management of patient distress.
Authors: Chiesa et al. (2021), Country: Italy, Lead: Medicine	To predict sedation needs during radiotherapy	Study design: Observational study; Setting: hospital; Data collection: multicomponent assessment tool using several measures e.g., pain distress-nursing observations, development-discomfort age score, medical-first medical evaluation etc.	Numbers: 99; Type: paediatric cancer patients with cognitive impairment; Gender: male = 51, female = 48; Age: median age was 7.5 years (range 1–21); Ethnicity: not reported	Boruta method (a random forest classifier) and elastic net	Fourteen features were predictive for anaesthesia e.g., patient age, emotional distress, level of collaboration, cognitive difficulties etc. Comprehensive assessment can help predict the need for sedation in paediatric cancer patients. This could be used to personalise treatment and management of childhood cancers.
Authors: Chung et al. (2021), Country: Taiwan, Lead: Computer science	To predict cancer nurse staffing requirements	Study design: Retrospective cohort study; Setting: National health insurance database; Data collection: data from the Taiwan Health Insurance Database	Numbers: 140518.7; Type: cancer patients; Gender: not reported; Age: not reported; Ethnicity: not reported	Applied fuzzy sets to system dynamic forecasting model	Supply of nurses for inpatient cancer services in 2027 is expected to be 20244, with a demand of 46542. Nursing staff gap of 26297. This type of modelling could help government plan and deliver nursing services in oncology.
Authors: Günther et al. (2022), Country: Switzerland, Lead: Medicine	To find cancer patients at risk of missing psycho-oncological treatment	Study design: Retrospective cohort study; Setting: hospital in Zurich; Data collection: 47 variables from 7318 cancer patient records in an electronic case file between 2011 and 2019	Numbers: training (70%, 5123) and validation (30%, 2195).; Type: cancer patients; Gender: female 3749 (51.2%) and male = 3569 (48.8%); Age: mean age = 63 years; Ethnicity: not reported	Random forest, support vector machine, decision trees, k-nearest neighbor, naïve bayes, gradient boost machine (GBM), logistic regression	Several variables predictive for missing psycho-oncological treatment such as not screened for distress, inpatient treatment <28 days, no psychiatric diagnosis, >65 years, etc. This approach may help identify patients at risk of missing referral to psycho-oncology.
Authors: (Im and Chee, 2011) Country: USA, Lead: Nursing	To develop a digital tool that can aid nurses' decisions about managing cancer pain for ethnic minority patients	Study design: cross-sectional descriptive design; Setting: online Internet dataset on cancer pain; Data collection: survey of cancer patients, four ethnic-specific online forums, 3-month evaluation of electronic decision tool with cancer nurses	Numbers: 480; Type: cancer patients with pain; Age: 51.92 (12.27); Gender: female = 381 (79.4%); Ethnicity: 148 whites, 105 Hispanics, 109 African Americans, 118 Asians	Fuzzy logic (fuzzy and crisp data sets) and natural language processing	Developing a decision support system for nurses using cancer patient data, fuzzy logic, algorithms, and computer technologies is feasible. Nurses suggested improving the display and data structure of the digital tool.
Authors: Jin et al.; Year: 2022, Country: China, Lead: Nursing	To develop and validate a predictive model for cancer-associated deep vein thrombosis (DVT)	Study design: retrospective cohort study; Setting: tertiary hospital; Data collection: data on cancer patients in an electronic medical record system	Numbers: 1035 of whom 231 had a DVT; Type: cancer patients who had a Doppler scan; Gender: not reported; Age: median age of 60 years; Ethnicity: all Chinese	Linear discriminant analysis, logistic regression, classification tree, random forest, and support vector machine	Five main predictor variables were D-dimer level, age, Charlson Comorbidity Index, length of stay, and history of venous thromboembolism. Linear discriminant analysis and logistic regression outperformed Khorana score. Nomogram and web calculator may help evaluate DVT risk to inform clinical decision making.
Authors: Kim et al., Year: 2019, Country: South Korea, Lead: Nursing	To examine if nursing narratives can predict postoperative length of hospital stay post-surgery for ovarian cancer.	Study design: case-control study - retrospective cohort; Setting: hospital; Data collection: nursing narratives in an EHR	Numbers: 33 patients; Type: surgery on ovarian cancer, long-stay (>12 days; n ¼ 13) and short-stay (12 days; n ¼ 20); Gender: all females; Age: aged over 65 years; Ethnicity: not reported	Recurrent neural network, long short-term memory	Words such as urination, food supply, bowel mobility, or pain were related to hospital stay in older women with ovarian cancer. The machine learning approach was able to predict the length of stay based on nursing narratives.
Authors: Koleck et al. (2021), Country: USA, Lead: Nursing	To compare symptom clusters among people with chronic conditions (i.e.,	Study design: retrospective cohort study; Setting: single medical centre; Data	Numbers: 133,977; Type: patients with chronic diseases; Gender: female	NLP application identified 56 symptoms	Pain most frequent symptom. Shared symptom clusters for heart failure and diabetes;

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Table 1 (*continued*)

Authors, Year, Country, Lead	Research aim(s) or objective (s)	Study design, Setting, Data collection	Participants	AI Intervention	Results/Outcomes
	chronic obstructive pulmonary disease (COPD), heart failure, type 2 diabetes mellitus, and cancer)	collection: nursing notes (N = 504,395; 133,977 patients) obtained a clinical data warehouse (inpatient, outpatient, and ED data)	51.5%; Age: median age 67 years; Ethnicity: white 33%, Black 10.4%, Unknown 53.5%, Other 3.3%		pain and other symptoms for COPD, diabetes, and cancer. Found shared and distinct symptom clusters that were established and novel across chronic conditions.
Authors: Lee et al. (2022), Country: USA, Lead: Nursing	To develop a model to classify ovarian cancer patient and caregiver needs	Study design: cross-sectional descriptive analysis; Setting: online health communities; Data collection: posts from the online Cancer Survivors Network (2006–2016)	Numbers: 853 online user postings; Type: ovarian cancer patients (n = 539), caregivers (n = 285), and unknown (n = 30); Gender: not reported; Age: not reported; Ethnicity: not reported	Natural language processing i.e., Bag of Words LP and logistic regression model	Information, social, psychological/emotional, and physical needs identified. AI model had a high level of accuracy for classifying top needs. There is potential to use online health communities to support a comprehensive needs assessment.
Authors: Meng et al. (2022), Country: China, Lead: Nursing	To develop predictive models for the risk of developing venous thromboembolism (VTE) in cancer patients in hospital	Study design: retrospective case-control study; Setting: Hunan Cancer Hospital; Data collection: Patient, tumour, treatment, and laboratory information obtained from hospital computer system (120 variables)	Numbers: 1100; Type: hospitalised cancer patients (340 patients (30.9%) in the VTE group); Gender: 44.09% male; Age: mean age 54.75[11.08] years; Ethnicity: not reported	Logistic regression, support vector machine, random forest, and extreme gradient boosting (XGBoost)	XGBoost model performed best. D-dimer level, diabetes, hypertension, pleural metastasis, and haematological malignancies most significant features. This approach improve assessment and management of VTE risk.
Authors: Olling et al. (2018), Country: Denmark, Lead: Medicine	To predict if prescription medication for odynophagia is required during external beam radiotherapy	Study design: mixed methods; Setting: hospital; Data collection: electronic radiotherapy records (131 patient cases), radiotherapy dosimetry data, patient interview data about medication need, treatment-related side effects etc, case reports from nurses and doctors' notes, and hospital electronic journals	Numbers: 131; Type: patients completing radiotherapy fraction for lung cancer, Age: aged 35–86; Gender: female n = 67 (51.1%); Ethnicity: not reported	Lasso and Elastic-Net Regularized Generalized Linear Models, Support Vector Machine (SVM), ML regression	Overall predictive performance was good but further validation of the models are needed in a clinical context. This approach could enable nurses to target high risk patients to ensure appropriate medication management prior to radiotherapy.
Authors: On et al. (2022), Country: South Korea, Lead: Nursing	To predict chemotherapy-induced adverse drug reactions (ADRs)	Study design: retrospective observational approach; Setting: tertiary teaching hospitals; Data collection: EHR data of 935 adult patients receiving 6812 chemotherapy cycles and 4 different regimens	Numbers: 935; Type: adult cancer patients; Gender: males 520 (55.6%); Age: mean 60.9 ± 12.1 (24–92 years); Ethnicity: not reported	Logistic regression, decision tree, and artificial neural network	Nausea-vomiting was the most common ADR, followed by fatigue-anorexia, peripheral neuropathy, and diarrhoea. Logistic regression model performed best with the area under the curve for six ADRs (range 0.67–0.83).
Authors: Park et al. (2015), Country: South Korea, Lead: Nursing	To assess the risk of infection in cancer patients having chemotherapy	Study design: retrospective study; Setting: university hospital; Data collection: patient and other data extracted from electronic medical records	Numbers: 732; Type: cancer patients receiving chemotherapy; Gender: male n = 381 (52%); Age: 134 were <50 years, 196 were 50–59 years, 190 were 60–69 years, 180 were 70–79 years, 32 were >80 years; Ethnicity: not reported	Decision tree and logistic regression	Predictive factors were alkylating agents, vinca alkaloid and underlying diabetes mellitus. Logistic regression showed higher sensitivity and classification accuracy and so is a better method to predict infection in patients having chemotherapy.
Authors: Solanti et al. (2022), Country: Iran, Lead: Health services and systems research	To develop a digital tool that predicts the demand of end-stage cancer home hospitalised patients	Study design: Not clearly described; Setting: charity organisation delivering palliative care; Data collection: data extracted from an information system at a cancer centre	Numbers: 12358 (number of patients reached 743 after cleaning); Type: cancer patients; Gender: male 52%; Age: range from 3 to 95 (most between 60 and 90 years old); Ethnicity: not reported	Long Short-Term Memory (LSTM)-based neural networks (one for individual patients and one for the population level)	AI models could forecast patient demand with good performance. This type of digital tool could assist in planning and delivering cancer palliative care services.
Authors: Takehira et al. (2011), Country: Japan, Lead: Pharmacy	To evaluate the perspectives of pharmacists and nurses about cancer patients' quality of life (QOL)	Study design: not clearly described; Setting: university hospital; Data collection: series of questionnaires on patients QOL, cancer therapy, general wellbeing	Numbers: 15, 8 and 18; Type: cancer hospital inpatients, pharmacists, and nurses; Gender: 8 females and 7 male patients; Age: age: 64.7 ± 7.2 years; Ethnicity: not reported	Artificial neural network (ANN) used to model QOL relationships	Predictive performance of the ANN was acceptable. Pharmacists and nurses evaluated patient's QOL using different information and reasoning.
Authors: van de Sande et al. (2021), Country: The Netherlands, Lead: Medicine	To predict whether patients need longer post-op care	Study design: single-centre retrospective cohort study; Setting: tertiary hospital; Data collection: data	Numbers:1677 episodes; Type: all adult patients in surgical oncology; Gender: 837 (50%) were	Logistic regression, gradient boosting, neural network, and random forest	Random forest model had the most accurate prediction on patient discharge post-operatively. This could help

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Table 1 (*continued*)

Authors, Year, Country, Lead	Research aim(s) or objective (s)	Study design, Setting, Data collection	Participants	AI Intervention	Results/Outcomes
		extracted from an EHR on pre-op assessment, patient characteristics, admissions, MDT notes, surgery details, medication, and clinical tests and assessments	men; Age: median age was 63; Ethnicity: not reported		hospitals plan and deliver surgical cancer care.
Authors: Vehviläinen-Julkunen et al. (2021), Country: Finland, Lead: Nursing	To explore the experiences and perceptions of people undergoing cancer treatment, using novel analysis techniques to provide rapid free-text data analysis	Study design: mixed methods; Setting: university hospital outpatient clinics; Data collection: qualitative questions from the National Cancer Patient Experience Survey and 7 focus groups (31 people with cancer)	Numbers: 208 (92 provided free-text comments); Type: people with breast, prostate, and lung cancer; Gender: 148 female (71.2%); Age: 20–54 years = 133 (63.9%) and 55–97 years = 37 (17.8%); Ethnicity: Finnish 74 (80.4%)	Sentiment analysis algorithm (NLP), random forest, linear support vector classifier, multinomial naive Bayes, and logistic regression	121 free-text comments (73.6%) on patient experiences were positive and 75 (38.5%) negatives. Communication was an indicator of quality whereas lack of psychological support was a barrier.
Authors: Wei et al. (2021), Country: China, Lead: Nursing	To develop a symptom-warning model to detect breast cancer-related lymphedema (BCRL)	Study design: cross-sectional study; Setting: tertiary hospital; Data collection: questionnaire on patients' sociodemographic data, clinical information from EHR	Numbers: 533; Type: postoperative breast cancer patients; Gender: 100% female; Age: average age of 58.0 ± 11.3 years; Ethnicity: not reported	Logistic regression, random forest, artificial neural network, support vector machine, classification and regression tree, and C5.0	Logistic regression model showed the best performance. The web application based on this model allows estimation of the likelihood of lymphedema, enabling real-time monitoring and treatment of breast cancer patients.
Authors: Wu et al. (2022), Country: China, Lead: Nursing	To predict the occurrence of breast cancer-related lymphedema (BCRL)	Study design: retrospective cohort study; Setting: cancer hospital; Data collection: data extracted from medical records, telephone interviews, and questionnaires which led to 48 variables, grouped into 5 feature sets	Numbers: 370; Type: patients post breast cancer surgery, 91 had BCRL (24.6%); Gender: all female participants; Age: mean age 49.89 years (± 7.45); Ethnicity: Chinese women (Han 300, 82.2%)	Naïve Bayes, k-nearest neighbor, support vector machine, logistic regression, and a multilayer perceptron (a type of neural network)	Logistic regression model achieved the best performance for BCRL. Most important variables for the models performance were the number of positive lymph nodes, BCRL on the same side as the surgery, a history of sentinel lymph node biopsy, a dietary preference for meat and fried food, and limited exercise.
Authors: Zeng et al. (2021), Country: China, Lead: Nursing	To predict postoperative complications among cancer patients	Study design: not clearly described; Setting: university hospital; Data collection: source not clear, a range of pre and post-op parameters used	Numbers: 175; Type: patients with liver cancer; Gender: 144 (82.29%) were male, and 31 (17.71%) were female; Age: patients were under 65 years old, average age 49.8; Ethnicity: not reported	Logistic regression, Decision tree classifiers, C5.0, Classification and regression tree (CART), Support vector machine, Random Forest (RF)	Random forest model gave the best performance from the decision curves analysis. Several features were predictive of post-op complications in liver resection patients including duration of operation, body mass index, and length of incision.

Abbreviations: Adverse drug reactions (ADRs); Artificial intelligence (AI); Artificial neural network (ANN); Breast cancer-related lymphedema (BCRL); Classification and regression tree (CART); Chronic obstructive pulmonary disease (COPD); Deep vein thrombosis (DVT); Distress Thermometer (DT); Electronic health records (EHR); Emergency Department (ED); Histogram of Oriented Gradients (HOG); Hospital Anxiety and Depression Scale (HADS); Logistic regression (LR); Long Short-Term Memory (LSTM); Multidisciplinary Team (MDT); Machine Learning (ML); Multilayer perceptron (MLP); Natural language processing (NLP); Quality of life (QOL); Random Forest (RF); Support Vector Machine (SVM); Venous Thromboembolism (VTE); Wong Baker Scale (WBS).

2021).

4. Discussion

4.1. Principal findings

This systematic review found numerous applications of AI in cancer nursing. A range of advanced computational techniques were employed across several areas of oncology, including breast, lung, prostate, ovarian, and general cancer care where patients receiving radiotherapy or chemotherapy were at risk of developing infection or experiencing venous thromboembolism. The algorithms were mainly tested on data from hospital EHRs to build models to increase the accuracy of predicting health outcomes. In some cases, models that used several machine learning techniques were developed and compared to assess which approach delivered the most robust predictive ability. However, few studies reported AI-based digital tools being used by cancer nurses working in oncology settings, either in hospital or the community, to inform clinical decision making, care delivery, and patient outcomes. This finding reflects AI research in nursing more generally, medicine, and other health disciplines, as there are few studies that examined AI based technologies with professionals in real-world healthcare settings (O'Connor et al., 2023; dos Santos et al., 2019). For instance, a scoping review of AI in primary care found that supervised machine learning methods were mainly developed or modified on community based datasets, with a smaller number of studies focusing on AI to support physician diagnostic or treatment recommendations for chronic conditions (Kueper et al., 2020). However, only potential benefits from AI were reported in this review as most of the included studies trained and tested algorithms, without implementing the predictive models into clinical practice in a real health setting.

Only one study, Im and Chee (2011) evaluated an AI-based tool with nurses to help them make better decisions about managing cancer pain, suggesting improvements to the design and functionality of the digital tool. However, its effect on clinical decision making and quality of patient care was not assessed. The impact of AI based digital tools in clinical practice settings has been investigated in other studies. Ginestra et al. (2019) developed an early warning score (EWS) system with machine learning algorithms to predict sepsis or septic shock. This was deployed in a large academic hospital in the United States with nurses and physicians, who received alerts from the EWS system about at-risk patients, but their perceptions of the AI based tool were poor as most reported no change in their understanding of patient risk and only a handful of alerts led to change in patient management. Furthermore, few randomized controlled trials of AI-based digital health interventions have been published which are needed to generate robust evidence of its effectiveness in improving outcomes (Angus, 2020). Other studies have examined implementation issues when integrating machine learning models into clinical practice and reported numerous socio-technical factors such as the unfamiliarity of AI among clinicians and lack of AI education, trust in the accuracy and utility of predictive models, and IT support among other issues that affected this process (Joshi et al., 2022; Sandhu et al., 2020).

The review also revealed that nurses led the research studies or actively participated in developing and testing AI algorithms in oncology, and in one case implemented and evaluated an AI based tool in clinical practice. However, in a few studies nurses were more passively involved or not included which reflects the findings of other reviews of AI in the nursing profession (von Gerich et al., 2022; Seibert et al., 2021). Although nurses often work in multidisciplinary teams and environments, particularly in acute hospital settings, Ronquillo et al. (2021) advocate for nurses to take a lead in the development and application of AI techniques such as machine learning and NLP in healthcare. This could help ensure that any predictive models and AI-based digital tools have clinical utility and take account of the workflow and workload of nurses in oncology, as nurses are the primary carer givers in clinical settings. Furthermore, AI tools for cancer patients were missing from the review but are under development (van Wijk, 2022), as predictive algorithms may support patient self-management and are being integrated into health apps, wearable and assisted living devices, and robotics. For instance, Battersby et al. (2018) used a patient-reported outcome measure (PROM) to develop and validate an online tool to predict postoperative bowel dysfunction to support cancer specialists and patients. This area of AI research is likely to expand in the future as more focus is given to supporting cancer patients to self-care at home.

The review also identified some limitations of AI in cancer nursing. These tended to focus on the quality of the underlying oncology datasets which were often from a single organisation and retrospective in nature. This may reduce the accuracy and generalisability of the predictive models, a drawback of AI that has been widely reported in the healthcare literature (Maddox et al., 2019). Others have highlighted the potential for algorithmic bias to create further inequalities in healthcare, if vulnerable populations are underrepresented in health datasets that are used to build predictive models which could influence clinical, managerial, and policy decision making (Garcia, 2016; Obermeyer et al., 2019). The review also found a need for more clinical validation of AI prediction models in oncology, a shortcoming that has been noted in other areas of nursing, medicine, and healthcare (Labarere et al., 2014; Dhiman et al., 2021; Dhiman et al., 2023). Few risks related to AI in cancer nursing were reported in the review. However, several issues have been raised such as clinical accountability when autonomous AI systems are used in oncology (Nagy et al., 2020), a lack of trust in some AI techniques that operate as a "black box" as there is limited transparency in how the final predictive model is built (Chua et al., 2021), and the cost of developing and implementing AI tools compared to the benefits that may be derived from them (Dlamini et al., 2020).

4.2. Future implications

- Designing and deploying AI-based digital tools with cancer nurses needs more rigorous research to determine if sophisticated algorithms can improve clinical and managerial decision making and patient outcomes across the spectrum of oncology services. In addition, most studies in the review were based in Asia or the United States with only a handful from Europe, indicating more investment may be needed to fund AI research in countries and regions where cancer nursing makes a significant contribution to oncology services.
- No studies were found that examined AI in relation to education or policy in cancer nursing, other areas of professional practice that would be useful to explore.
- The barriers and facilitators to introducing AI-based tools in cancer nursing in various acute and primary care settings including with patients at home would be important to research further. This could improve our understanding of the mechanisms by which these novel computational techniques can be deployed in real-world, complex care settings and the impact AI may have on the workflow and workload of nurses in oncology.
- Educating cancer nurses and nursing students about algorithms and predictive modelling is also important (O'Connor, 2022), so the profession can start to apply AI techniques and tools in oncology nursing practice, research, education, and policy.
- Cancer nurses could become involved in co-designing these technologies with patients and carers to enable high-quality AI tools to be developed that support their needs (Booth et al., 2021).
- Reporting guidelines have been published for AI prediction models (Collins et al., 2015; Luo et al., 2016), and there are protocol guidelines for clinical trials of AI interventions (Cruz Rivera et al., 2020), along with a framework for evaluating the implementation of AI based tools in healthcare (Reddy et al., 2021). Cancer nurses should use these when planning, conducting, and reporting AI research.
- Given the ethical and legal risks that accompany the use of AI, cancer nurses should become involved in the governance of AI initiatives to ensure these computational techniques are applied appropriately in healthcare (Gowda et al., 2021). More research on the limitations and risks of AI in cancer nursing is also needed.

4.3. Strengths and limitations of the review

Strengths of the systematic review include the use of several biomedical databases and independent reviewers who screened studies against inclusion criteria, along with employing best practice reporting international guidelines such as PRISMA. However, a number of limitations are also present. Publications such as conference proceedings, theses, and discursive articles were not included meaning some pertinent literature related to cancer nursing and AI may have been missed. The included studies hailed mainly from Western developed nations, with the exception of China and Iran. AI may affect oncology services in low- and middle-income countries differently due to a myriad of socio-cultural and geo-political factors. Hence, the findings of the review should be interpreted with some caution.

5. Conclusion

The review showed AI is being utilised in cancer nursing, but more workforce education and development is needed to prepare nurses to apply predictive algorithms to oncology datasets to try to improve professional practice, patient care, and the delivery of cancer services. More rigorous research that evaluates the real-world impact of AI tools on oncology nursing practice is also needed, along with examining the limitations and risks of these advanced computational techniques. This could help ensure that the potential of AI is maximised in cancer nursing to the benefit of patients and the profession.

CRediT authorship contribution statement

Siobhan O'Connor: Conceptualization, Formal analysis, Methodology, Writing – original draft. **Amy Vercell:** Formal analysis, Validation, Writing – original draft. **David Wong:** Methodology, Validation, Writing – original draft. **Janelle Yorke:** Formal analysis, Writing – review & editing. **Fatmah Abdulsamad Fallatah:** Formal analysis, Writing – review & editing. **Louise Cave:** Data curation, Formal analysis, Writing – review & editing. **Lu-Yen Anny Chen:** Data curation, Formal analysis, Writing – review & editing.

Declaration of competing interest

All authors declare no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ejon.2024.102510.

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