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Review

Artificial intelligence empowered digital health technologies in cancer survivorship care: A scoping review

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ABSTRACT

Objective: The objectives of this systematic review are to describe features and specific application scenarios for current cancer survivorship care services of Artificial intelligence (AI)-driven digital health technologies (DHTs) and to explore the acceptance and briefly evaluate its feasibility in the application process.
Methods: Search for literatures published from 2010 to 2022 on sites MEDLINE, IEEE-Xplor, PubMed, Embase, Cochrane Central Register of Controlled Trials and Scopus systematically. The types of literatures include original research, descriptive study, randomized controlled trial, pilot study, and feasible or acceptable study. The literatures above described current status and effectiveness of digital medical technologies based on AI and used in cancer survivorship care services. Additionally, we use QuADS quality assessment tool to evaluate the quality of literatures included in this review.
Results: 43 studies that met the inclusion criteria were analyzed and qualitatively synthesized. The current status and results related to the application of AI-driven DHTs in cancer survivorship care were reviewed. Most of these studies were designed specifically for breast cancer survivors' care and focused on the areas of recurrence or secondary cancer prediction, clinical decision support, cancer survivability prediction, population or treatment stratified, anti-cancer treatment-induced adverse reaction prediction, and so on. Applying AI-based DHTs to cancer survivors actually has shown some positive outcomes, including increased motivation of patient-reported outcomes (PROs), reduce fatigue and pain levels, improved quality of life, and physical function. However, current research mostly explored the technology development and formation (testing) phases, with limited-scale population, and single-center trial. Therefore, it is not suitable to draw conclusions that the effectiveness of AI-based DHTs in supportive cancer care, as most of applications are still in the early stage of development and feasibility testing.
Conclusions: While digital therapies are promising in the care of cancer patients, more high-quality studies are still needed in the future to demonstrate the effectiveness of digital therapies in cancer care. Studies should explore how to develop uniform standards for measuring patient-related outcomes, ensure the scientific validity of research methods, and emphasize patient and health practitioner involvement in the development and use of technology.

Introduction

Cancer is the second cause of mortality worldwide, as recent reports indicated that there were approximately 18.1 million new cancer cases and 9.6 million cancer-related deaths worldwide in 2020.[1] The increase in cancer incidence and decrease in mortality compared to 2018 has led to a rapidly growing population of cancer survivors. As the landmark report *From Cancer Patient to Cancer Survivor, Lost in Transition* highlighted,[2] traditional healthcare delivery model which have put more attention to first-line treatment for patients with cancer and has no longer

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able to satisfy the increasingly and variously requirements of cancer survivors in addition to lengthening life span. Health care professionals are shifting their concerns to post-acute care and seeking for innovative model.[3]

In this context, The Institute of Medicine (IOM)[4] recommends that survivorship care planning (SCP) for every cancer survivors, contains the following areas (1) provide surveillance for recurrences or new cancer regularly, (2) management of adverse reactions or physical effect, (3) health behaviors promotion and general healthcare, (4) supporting patients to cope with adverse reactions of physical or psychological during the disease progression, late effects after acute treatment successfully, and (5) improving their quality of life ultimately. However, in general, the complex composition of a SCP team makes it difficult to ensure effective communication and collaboration between members.[5] In addition, concerning restrictions of local policy, limitation of time and space, and shortage of human resource, ability or continuity of SCP are difficult to ensure.[6] Therefore, there is an urgent need to seek new SCP models as supplementary, replace a part of human resources.

As a subset of Internet Technology, digital health technologies (DHTs) which consist of both software and hardware techniques, has been broadly used in healthcare domain.[7] Over the past decade, there has been amount of research demonstrated that DHTs not only accepted by patients and healthcare providers but it also can improve care practice, support clinical decision, and facilitate communication, suggesting that it is a promising way to enhance the quality of care.[8] However, traditional DHTs mostly using telemedicine platforms as a medium (eg., Telehealth) have produced certain effects in realizing real-time doctor-patient communication and distance health education for patients. Their relatively single function limited their usage in broadly clinical practice. First, traditional DHTs can only provide simple treatment services and lose their advantages when encountering relatively complex clinical scenarios. Second, heavy reliance on healthcare providers' knowledge during delivery process is also a barrier. Lastly, they can hardly meet the multiple requirements of the current cancer survivors.[8]

Artificial intelligence (AI) can optimize problems and meet requirements above. AI generally refers to the ability of a computer to demonstrate intelligent behavior, the development of which requires three essential foundations—*Data*, *Computing power* and *Algorithms*, which can corresponding to *Wearable Devices*, *Cloud computing*, and *Machine Learning* techniques respectively.[9] Unlike traditional DHT, the intelligent algorithm can extract key information from a large amount of diverse patient data and classifies and summarizes general patterns (ie., simulates the thinking process of the human brain), thus achieving the function of replacing part of human work.[10] Consequently, AI empowered DHTs,

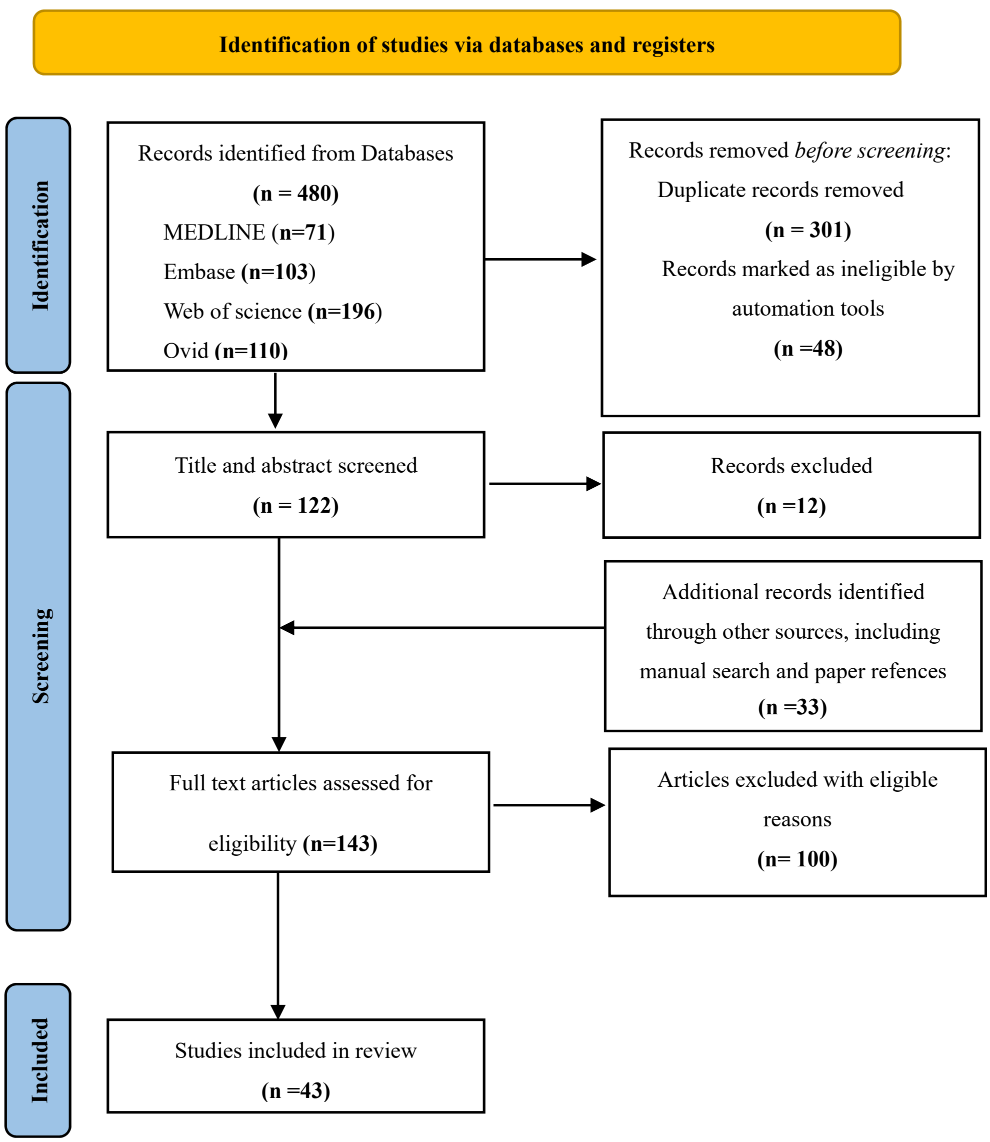

Fig. 1. PRISMA flowchart. PRISMA, Preferred Reporting Items for Systematic Evaluation and Meta-Analysis.

combined with behavioral science and evidence-based guidelines, will to some extent change the traditional cancer medical care model and provide more accurate, affordable, and convenient medical and health services to a large group of cancer survivors.[11] Therefore, this review aims to classify and describe current clinical application scenarios of AI-empowered DHTs and evaluate the feasibility and effectiveness of current AI-empowered DHTs applied in cancer survivorship care.

Methods

Search strategy

This scoping review was conducted under the guidance of the Preferred Reporting Items for Systematic Evaluation and Meta-Analysis (PRISMA), and the flow of the process is shown in Fig. 1.

The Web of science, PubMed, Embase (Ovid, Wolters Kluwer), Cochrane Central Register of Controlled Trials, IEEE-Xplore, and other databases were searched from December 2010 to April 2022. This period was chosen because of the rapid development of digital technology and the emergence of research related to AI and DHTs. The search terms and search formulas are as follows:

Pubmed, Embase, Ovid and IEEE = ("cancer care" OR "cancer survivorship care" OR"cancer supportive care") AND ("AI" OR "artificial intelligence" OR "machine learning" OR"deep learning" OR"nature language processing" OR"expert system"OR "digital healthcare" OR "digital technology")

WoS: ((((TS = (artificial intelligence* or machine learning)) AND TS = (cancer)) AND TS = (care)) NOT (TS = American Indian)) NOT (TS = aromatase inhibitor).

Additional search terms were included based on synonyms of these keywords. See Supplementary Appendix for search strings).

Eligibility criteria

We reviewed articles published in journal proceedings over the past decade. In the initial screening of titles and abstracts, any literature that met the following criteria was included:

(1) Papers written in English or Chinese
(2) The relevant stakeholders of SCPs with AI empowered DHTs are cancer survivors (both adults and childhoods), caregivers (formal or informal), oncologists, clinical specialists, and healthcare practitioners during the whole anticancer treatment period.
(3) In order to make a consensus of SCPs' definition and required elements, we used the Cancer Survivorship Care Framework conceptual model proposed by the NIC,[12] which contains the following five core components: (i) prevention and monitoring of cancer recurrence or metastasis; (ii) monitoring and management of physical symptoms; (iii) psychosocial monitoring and management; (iv) promotion of healthy behaviors and improvement of undesirable behaviors; (v) achieving patient participation. Any intervention or service yield to 5 domains above considered eligible to include paper. Additionally, interventions supporting palliative care were excluded because these are beyond the scope of survivorship care.
(4) The DHTs described in the eligible papers should be conformed to Informatic, Digital, or Computer science which assisted by AI. Therefore, we clearly defined the terms AI, digital healthcare technology[13]:

Since there is no conclusive definition of a specific AI and its sub-domains related to health or care, various types of AI systems or approaches, ranging from explicit categories (ML, expert systems, hybrid systems), to any hybrid algorithm combining one or more of the two, such as machine learning or expert systems (eg., intelligent systems or AI in healthcare), are considered to be eligible.

Studies included in the review must met any one of the above criteria for research purposes.

Data extraction and integration

Two reviewers (PLC, WXR) initially reviewed the title and abstract independently, eliminating irrelevant literature and then reviewing the retained studies in their entirety. In case of disagreement, the discussion seeks consensus and is judged by consulting a third reviewer (ZYL). Two reviewers (PLC, LY) used the Critical Assessment Skills Program for Bias Tools (QuADS-Quality assessment with diverse studies checklist, 2021) to determine the quality of included studies. This study used software Zotero to manage the literature and Microsoft Excel to extract key information from the included literature and apply it to the collection and analysis of structured data.

Literature quality evaluation

All manuscripts included in this review were assessed for quality using the QuADS-Quality assessment checklist.[14] We chose the QuADS-Quality assessment with diverse studies checklist because it had the broadest applicability to the articles we included for review. The results of the quality evaluation will be added to the annex as Supplementary C.

Results

Overview of included studies

The retrieval search generated 480 records. After reviewing title and abstract, 143 literatures were retained. 43 studies were identified through a full-text review. Three additional studies were identified through reference searches and would therefore be included in the above 43 publications.

The population: 60% of the included studies were designed for patients with a single tumor. Two of the studies were for head and neck cancer; the others were for melanoma. Of the studies in patients with combined multiple cancers, 1 study explored breast and prostate cancer and 1 study was for lung, breast, or colorectal cancer. The remaining eight studies included several tumor types, such as patients living with any type or stage of cancer or those with solid tumors receiving chemotherapy at an ambulatory oncology clinic. Notably, AI and DHT research for breast cancer survivors has been trending hot and dominant in recent years, with a total of 28 studies.

Study characteristics

Current usage of artificial intelligence in cancer survivorship care

43 studies showed current landscape and applied scenario of AI used in cancer survivorship domain. Most of the studies were conducted in Europe ($n = 16$)[10,15–27], Asia ($n = 12$)[28–40], USA ($n = 12$)[41–52] followed by Middle East ($n = 2$)[53,54], and UK ($n = 1$)[55] Supplement A presents an overview of these studies' characteristics. Based on the various clinical application and potential functions, the studies can be divided into following categories, they are *1. Cancer recurrence or secondary cancer prediction; 2. Clinical decision* support*; 3. Cancer survivability prediction; 4. Population or treatment stratified; 5. Anti-cancer treatment induced adverse reaction prediction; 6. Symptom stress (e.g. anxiety, pain, insomnia, lymphedema, etc.) prediction; 7. Symptoms monitor and management; 8. Behavior change and health promotion; 9. Communication and Information improved; 10. Comprehensive cancer survivorship platform and system; 11. Care process mining and 12. Others.* Table S1 shows the classification and specific description of AI used in cancer survivorship care domain. However, we acknowledged that this classification is somewhat subjective; boundaries among concepts are blurred and crossed as it is hard to detach them from each other absolutely.

Prediction is still main function achieved by ML, 12 studies included in this review addressed the postoperative complications among surgical cancer survivors, prediction of adverse effects of cancer-related treatments and medications, prediction of survival of cancer patients, risk of cancer recurrence, and prediction of quality of life and treatment outcomes. 4 of these studies were from China, 3 studies were from the United States, and the remaining studies were from the United Kingdom, Turkey, Korea, Poland, and Iran.

Among Chinese studies, two focused on breast cancer, in which Gu, Dongxiao et al.[32] developed a case-based integrated learning system for breast cancer recurrence prediction that provides the interpretation of prediction results, making them easy for physicians to understand while assisting them in making the best decisions for their patients, and another study[36] developed a symptom warning model for breast cancer-related lymphedema by identifying 24 lymphedema-related predictors through six machine learning algorithms with fair sensitivity specificity, but the validity of the model still needs to be validated in a larger population. One study[37] was designed for patients undergoing thyroidectomy to explore the causes of their reduced quality of life and the other[51] to identify subsequent individualized treatment regimens by making predictions about clinical endpoints in patients with advanced cancer to avoid overmedication that increases patient suffering.

Of the three studies,[43,48,50] from the United States, were conducted to construct models for the risk of adverse effects caused by chemotherapeutic agents and one used machine learning algorithms to predict the results of TUG tests and their association with quality of survival in elderly cancer surgery patients.

A study[55] from UK proposes a comprehensive decision support framework to assist clinical oncologists in the prognostic assessment of breast cancer patients undergoing surgery, which can be delivered through a web interface.

The study[53] from Turkey was published in 2016, relative early, in which researchers used data generated from cancer cell lines to provide a testbed for machine learning algorithms and to predict the response of cancer cells to different agents, thereby improving the prediction of drug response of cancer cell lines. Korean[29] researchers similarly developed the prediction models for various chemotherapy regimen-related adverse reactions (ARDs).

Polish scholars,[56] on the other hand, used dynamic Bayesian networks to develop health state networks and treatment effect networks for chronic lymphocytic leukemia patients to predict changes in their health status and disease progression over time.

DHTs applied in cancer survivorship care practice

As it is increasingly recognized that there is a need to better support patients once their treatment ended, so health professionals have started to explore the role that technology can play in ensuring services are cost effective. More and more health professionals realized that the DHTs have an adjunctive role in cancer survivorship care practices and its potential to optimize the provision and coordination of services. Based on the various clinical application and potential functions, the studies can be divided into following categories, Table 1 shows the classification and specific description of DHTs used in cancer survivorship practice domain. And more specific details in Supplement B.

(1) **Symptom management and monitoring** can be further divided into home, inpatient, outpatient, and other according to different settings. In the management of symptom monitoring in patients with cancer at home, some studies focused on patients with cancer during treatment and several studies have addressed the management of adverse reactions during cancer treatment (including chemotherapy, radiotherapy, and adverse drug reactions[57–79]) for monitoring. Followed by 13 studies of cancer comorbid symptoms[80–93] with 10 studies focused specifically on cancer-specific pain,[57,59,70–78] 13 studies examined the impact of novel DHTs on the psychosocial state of patients with cancer,[89–110] and 6 studies explored treatment adherence in addition to symptom monitoring and management for patients with cancer at home.[55–61] DHTs can also be applied in the inpatient setting for symptom monitoring and management in oncology patients. A monitoring system designed and developed specifically for bone marrow transplant patients to improve bedside symptoms,[77] the software has a built-in daily PROs assessment board that can monitor and manage 16 common adverse symptoms experienced by patients receiving stem cell transplants, automatically generating email reports and providing links to designated nurses. Another digital health tool undergoing usability testing, "The Color Me Healthy App,"[89–92] is a game-based app designed to improve symptom management for children with cancer during hospitalization. Both of these apps are undergoing clinical usability testing, so further research is needed to determine their effectiveness. In addition to home and inpatient setting, DHTs can also be used to collect data from patients on an ongoing basis before the start of the consultation ($n = 2$), allowing for professional clinical monitoring and assessment in advance, in order to provide a systematic and effective reference for the subsequent organization of symptom discussions, the implementation of the above functions usually requires more complex internal algorithms and is mostly supplemented externally with hardware technologies such as symptom trackers, of which the representative programs are Interacct[93] and SAMI[93], respectively. In addition, new technologies for symptom monitoring ($n = 4$) have emerged in recent years, such as new sensors (sensors)[94–96] and miniature intelligent robots[97] that provide new ideas for applied research on symptom monitoring in patients with cancer.

(2) **Decision making and Information sharing**, DHTs have the potential to facilitate information flow and improved patient-centered treatment decision-making.[98] It could offer a better usage of resources by making consultations more efficient and effective and provide the patient with more opportunity to discuss options with family and friends, consider complex demands and possible consequences. Clinical decision and information sharing tools (CDTs)[91] are examples of educational resources that can be used to increase relevant knowledge and skills. As a result, decisional support tools have been developed to assist patients in the decision-making process and increasingly have been adapted to a digital format.

(3) **Survivorship and Follow-up care**, Survivors who chose to return to their community for follow-up care were followed using a coordinated care approach between the treating oncologist and the primary care provider to provide continuity of care. Survivors with a more complex risk profile or those diagnosed with a less prevalent cancer (eg., pancreatic cancer) were not transitioned to a disease specific survivorship care program. The total of 17 studies[114] on assisted cancer survivorship practices and follow-up care included in this study served to improve health status, enhance quality of life, reduce caregiver burden, and enable

Table 1
Classification and specific description of DHTs.

No.	Classification	Specific description
1	Symptom management and monitoring	DHTs are multifunctional and potentially mutually beneficial, providing insightful symptom data via patient reported outcomes to assist clinicians' decision-making, while also acting as a useful tool for patients to monitor and self-manage their own symptoms.
2	Decision making and Information sharing	Digital health has the potential to facilitate enhanced information flow and improved patient centered treatment decision-making
3	**Survivorship and Follow-up care**	Survivors who chose to return to their community for follow-up care were followed using a coordinated care approach between the treating oncologist and the primary care provider to provide continuity of care

telemedicine. Above all, 7 of them are via APP, 6 via web, and 4 via both web/APP and wearable devices. In the studies with interventions via APP alone. The populations included melanoma,[107] breast cancer,[108] lung cancer,[109] gynecologic tumors,[110] prostate cancer,[111] colon cancer,[112] and cancers that did not distinguish between disease types.[113] The most frequent interventions through APPs are to improve the quality of life of patients, to relieve adverse emotions, such as anxiety and depression, and to improve health status. 6 of these demonstrated[107–113] that interventions via the app were effective and of great value, while helping to improve clinical workflow and also removing barriers and limitations to access to specialty care. 1 of the studies of patients with colon cancer[113] indicated that the intervention via the app was not statistically significant versus the offline approach. Among the study of intervention through webpage, the study populations were patients with cancer,[62,67,81,114] prostate cancer,[61] and ovarian cancer,[77] respectively, and the feasibility of observing patients through the intervention and the impact of the intervention on quality of life, all of the above studies showed significant statistical significance, proving that nursing intervention for cancer life through website can effectively improve the quality of life of patients with cancer. The intervention population through both web/app and wearable devices are patients with gynecological cancer,[79] advanced gastric cancer,[72] and cancer patients.[64,65] The patients are tested with wearable devices while the intervention is carried out to understand the patients' condition in time,[70] which helps patients' symptom management and improve their quality of life as well as health status.

In summary, DHTs provided in the study can be broadly classified into the following three categories based on the various application: *1. Delivered Information/Health Education*, *2. intervention applications providing behavior change aspects*, and *3. patient symptom scores involving psychosomatic symptoms such as pain scores, anxiety, and depression.* However, most of the above studies involving DHTs are still in the prototype development stage, involving a small range of patient populations, and only very few (eg. Oncokmpas, ASyMS) have been studied in other cancer populations. Same as AI techniques, breast cancer survivors still be the dominate position in all studies and rapidly becoming a growing hot spot within the field.

The results of quality appraisal for eligible studies

The item 11 get the highest score for qualified researches used the proper analysis method to reach their aim. The second score of the total is item 4 for most of study designs are fit to their aims and author gave sufficient reasons for the designs. The lowest one is item 12 for most of studied was in development phase, not at application stage yet. In the future, we need to pay more attention to the clinical use of AI-driven care services for cancer survivors, to study its clinical acceptance and applicability as well as to explore its potential ethical and moral problems and ethical review standards, so as to better reflect the benefits for users.

Discussion

AI-empowered DHTs enhanced cancer care and improved patient outcomes across multiple areas

Upon review, as mentioned in prior literature reviews[7,70,115] this review concludes the similar conclusions that AI-empowered DHTs in patients with cancer co-exists with risks and benefits. In addition, follow-up using technology is acceptable to patients with cancer, is clinically safe, and can improve health knowledge and self-management.

However, it should be concerned that although AI-enabled DHTs may change the core nature of medical services, the resulting transformative effects are still accompanied by ethical risks, including but not limited to the validity of existing evidence, the fairness of results, and accountability for harm caused by algorithms.[116] Furthermore, there is no consensus on the potential of AI-driven health technologies to enhance nursing practice since the key ideological and ethical nature of nursing practice, as well as the role of decision-making, still needs to be considered.[5] The amplified understanding of the opportunities offered by AI applications in the context of delivering ethical and transparent nursing care remains uncertain. In addition, past studies have reported potential challenges affecting digital health implementation, such as technical issues, lack of technical knowledge, and data security, which need to be considered when planning future studies.[117] A recent systematic review concluded[118] that digital supportive care and general digital health interventions should implement a range of strategies. O'Connor et al[119] suggest that increasing public awareness of different technologies and understanding of how they work, personalized care, clinical certification of interventions, increasing attention to health literacy, and protecting the privacy of personal information are areas of focus for future research. Based on the key areas of DHT application in cancer survival and care mentioned in previous reviews, future research should further explore the participant feedback mechanism to promote the co-design of digital interventions; second, it should ensure the transmission efficiency of relevant health care information; Finally, it should explore how to integrate the concepts and practices of survival planning services in all stages of the cancer care pathway.[120] AI-based DHT intervention models should be guided by a scientific theoretical framework that not only articulates expected outcomes and the tools to measure them but also encompass the intervention process to achieve the expected outcomes. However, most of the studies included in this paper did not address the issue of consistency of patient-reported outcomes, and most of the studies used pre or pro test designs and self-reported outcomes, which resulted in large heterogeneity between them, so no further inferences can be made. This may be in part because one of the main challenges in developing evidence-based digitally supported cancer treatment interventions is the apparently faster pace of technology development than the lengthy process of conducting and evaluating clinical trials.

Clinical practice hardly keep up with the speed of technology iteration

This review descripted characteristics and features about the application of AI-empowered DHTs in cancer survivorship care and management. Digital technology-based cancer care management has been implemented where necessary and is becoming a popular healthcare delivery format.[121] Three recommendations giving for future work to support cancer survivorship care and management: (1) nurses must understand the workflow of AI digital technologies that they used; (2) patients with cancer need to be meaningfully involved in all stage of development of AI DHTs; (3) exploring more potential applied settings in cancer survivorship care services.

Our quality assessment indicated that there is an urgent need to make an agreement on clinical outcome measures, increase comparability between studies, finally improve the quality of original research and randomized controlled trials. In addition, before 2011, none of included studies, disappointingly, cite any criterion for their research. And only 2 included publications[17,122] cite the CONSORT Digital Health Checklist published in 2011. Therefore, in future investigation, it might be recommend to use standardized report criteria or checklist to ensure the quality of research. Beyond that, there' still concern hovering on such topic, as Dickinson's comments on BMC Cancer remain sobering in 2022: “Considering the explosion of technological innovation in recent years, the number of randomized trials is surprisingly low. This may be because technology is advancing so rapidly that potential innovative technological interventions are obsolete before they are mature enough to allow for randomized trials.” insight above still persisted in current situation anyway.

Strengths and weaknesses of this study

Although this review provides a quality assessment for studies, the few included studies suggest that there may be significant literature in the feasibility of Phase 1 or 2. Although 43 studies were included in the first part which described the brief landscape of SCP applied settings, the results of the interventions were too heterogeneous to perform a meta-analysis. Due to the nature of this review, there were also heterogeneous populations, variable outcome measures, variable study quality, and methodological limitations. The study found that current studies lack evidence of clinical benefit, and it is difficult to draw conclusions and synthesize studies with inconsistent outcome measures, so there is an urgent need for a standardized measurement method to standardize measurement results. Therefore, the CONSORT Digital Health Checklist[54,123] is recommended for review of relevant research. Meanwhile, this review is limited to studies written in English and Chinese. As a result, research papers published elsewhere in the world risk being missed. As with many studies in oncology, this review found that there is a lot of research in breast cancer, and there is a need for relevant research in other areas of cancer. Finally, as most of the included studies were conducted in the United States and Europe, it is unclear whether the findings of these studies can be generalized to other countries, especially developing countries.

Implications for future research

As survival rates for many cancer types continue to increase, a better life with cancer has gained a greater relevance. The future of AI empowered digital health in oncology supportive care presents a range of novel and exciting possibilities. There is a need to assess the efficacy and efficiency of digital interventions in real-world conditions and standardize a core set of results included in all studies to facilitate comparisons between interventions and AI empowered digital technologies.

Conclusions

Although AI-based DHTs can improve cancer care and management to a certain extent, improve health-related quality of life, and have shown a role in reducing the burden of symptoms. However, the use of AI-based DHTs in the field of cancer care is not widespread, and its effectiveness needs to be further tested, requiring more obvious, higher-quality research evidence and clearer reporting than current randomized controlled trials to clarify. Future research should focus on using valid and standardized outcome measures, methodologically improving the rigor of the research carried out, formulating relevant policies, and issuing corresponding guidance documents, to facilitate patient and health professional engagement in AI-based DHTs.

Declaration of competing interest

None declared.

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Appendix A. Supplementary data

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