Oncology

Oncology and Informatics – Review

Oncology 2025;103:69–81
DOI: 10.1159/000540494

Received: March 31, 2024
Accepted: July 16, 2024
Published online: July 25, 2024

Integrating Artificial Intelligence-Driven Wearable Technology in Oncology Decision-Making: A Narrative Review

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Keywords

Wearable technology · Oncology · Decision-making · Precision medicine · Artificial intelligence in medicine

Abstract

Background: Clinical decision-making in oncology is a complex process influenced by numerous disease-related factors, patient demographics, and logistical considerations. With the advent of artificial intelligence (AI), precision medicine is undergoing a shift toward more precise and personalized care. Wearable device technology complements this paradigm shift by offering continuous monitoring of patient vitals, facilitating early intervention, and improving treatment adherence. The integration of these technologies promises to enhance the quality of oncological care, making it more responsive and tailored to individual patient needs, thereby enabling wider implementation of such applications in the clinical setting. ***Summary:*** This review article addresses the integration of wearable devices and AI in oncology, exploring their role in patient monitoring, treatment optimization, and research advancement along with an overview of completed clinical trials and utility in different aspects. The vast applications have been exemplified using several studies, and all the clinical trials completed till date have been summarized in Table 2. Additionally, we discuss challenges in implementation, regulatory considerations, and future perspectives for leveraging these technologies to enhance cancer care and radically changing the global health sector. ***Key Messages:*** AI is transforming cancer care by enhancing diagnostic, prognostic, and treatment planning tools, thus making precision medicine more effective. Wearable technology facilitates continuous, noninvasive monitoring, improving patient engagement and adherence to treatment protocols. The combined use of AI and wearables aids in monitoring patient activity, assessing frailty, predicting chemotherapy tolerance, detecting biomarkers, and managing treatment adherence. Despite these advancements, challenges such as data security, privacy, and the need for standardized devices persist. In the foreseeable future, wearable technology can hold significant potential to revolutionize personalized oncology care, empowering clinicians to deliver comprehensive and tailored treatments alongside standard therapy.

Plain Language Summary

This review paper explores how wearable devices and artificial intelligence (AI) are revolutionizing cancer care. Wearable technology, like smartwatches and biosensors, allows for continuous monitoring of vital signs, helping clinicians detect issues early and ensure patients follow their treatment plans. AI

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further enhances this by analyzing the data from wearables to offer precise, personalized care. The integration of these technologies can improve patient outcomes by monitoring activity levels, predicting chemotherapy tolerance, and tracking biomarkers. Despite their promise, challenges such as data privacy, standardization, and regulatory issues need to be addressed. Looking ahead, wearable technology is set to become a standard part of personalized cancer care, enabling better treatment planning and early intervention. It offers a promising future where treatments are more tailored and effective, improving the overall quality of oncology care.

Introduction

Clinical decision-making in oncology is a significant aspect of patient care, ranging from assessing treatment options to participating in clinical trials, symptom management, and diagnostic tests. It involves a multifaceted assessment encompassing various disease-related factors such as histology, genomic data, patient demographics like age, logistical considerations, and patient preferences. These factors greatly influence the selection of treatment methods, which can further affect patient tolerance and treatment outcomes. Artificial intelligence (AI) has been an instrumental transformational force in recent times, providing unprecedented assistance in traversing this intricate landscape. AI is already reshaping the future of oncological care with a variety of diagnostic and prognostic tools, ranging from radiodiagnosis, histopathology, genomics, radiotherapy, targeted therapy, remote monitoring, compliance, and much more [1]. The integration of AI into oncology therefore spans diverse domains, for instance, analysis of radiological imaging for early detection and characterization of tumors, such as in the case of mammography and MRI interpretation [2]. Additionally, AI-powered predictive genomics models aid in treatment planning by forecasting disease progression and response to therapies, thereby optimizing clinical decision-making. AI has greatly advanced targeted therapy by aiding in identifying certain molecular targets for individualized treatment plans, thus enhancing the precision and efficacy of oncological interventions.

Wearable devices hold immense potential in effectively integrating into patient monitoring protocols, facilitating real-time assessment of treatment efficacy, adherence, and compliance. Furthermore, wearable technology can predict not only cancer-related issues but also other health problems and vital parameters, allowing for early intervention. This personalized approach not only helps patients but also helps clinicians understand diseases better, so they can customize treatments based on each patient's needs. In this review, we explore the utility of wearable device technology in oncology, elucidating their role in integration into clinical settings. The review starts with an introduction to wearable technology and types of data that can be obtained, followed by its vast applications in oncology and lastly, significant challenges to consider and future perspectives.

Utility of Wearable Device Technology in Health Research

Wearable device technology refers to the accessories/gadgets that can be worn on the body to track various bodily parameters. Examples include smartwatches, biosensors, fitness trackers, headphones, smart clothing, AI hearing aids, smart contact lenses, smart jewelry, etc. [3, 4]. The use of wearables has been around for many decades; for instance, Holter monitor, a medical sensor used to measure electrical activity of the heart dates back to the 1960s. Since then, there has been a rapid rise in utilizing such tools in healthcare ranging from graphene-based biosensor for bacterial detection to smart face mask to monitor respiration and much more [5]. The integration of wearable device technology in oncology research has emerged as a revolutionary approach, transforming collection methods, analysis, and monitoring of patient data. Wearable devices enable continuous and noninvasive monitoring of a plethora of physiological markers or vital parameters, which further offers a comprehensive and time-efficient view of the disease status and patient response. They promote greater compliance and engagement in patients which results in improved adherence to treatment and, by analyzing real-time data, can lead to better personalized treatment strategies [6].

Different Types of Sensors Integrated in Wearables

As wearable platforms evolve, each iteration sees devices becoming smaller and integrating more sensors, enabling continuous collection and storage of extensive data. The changing landscape of healthcare delivery thus necessitates adjustments to current data acquisition methods to effectively incorporate AI-based smart technology. Furthermore, they can continuously track data hands-free, requiring minimal charging time and saving time in the long run. The sensors are of greatest significance as they are the key components used for storing and tracking the data. While there are variable types of sensors, built-in sensors are at rise in the currently available devices. To exemplify, in order to track physical activity, a 3-axis accelerometer, altimeter,

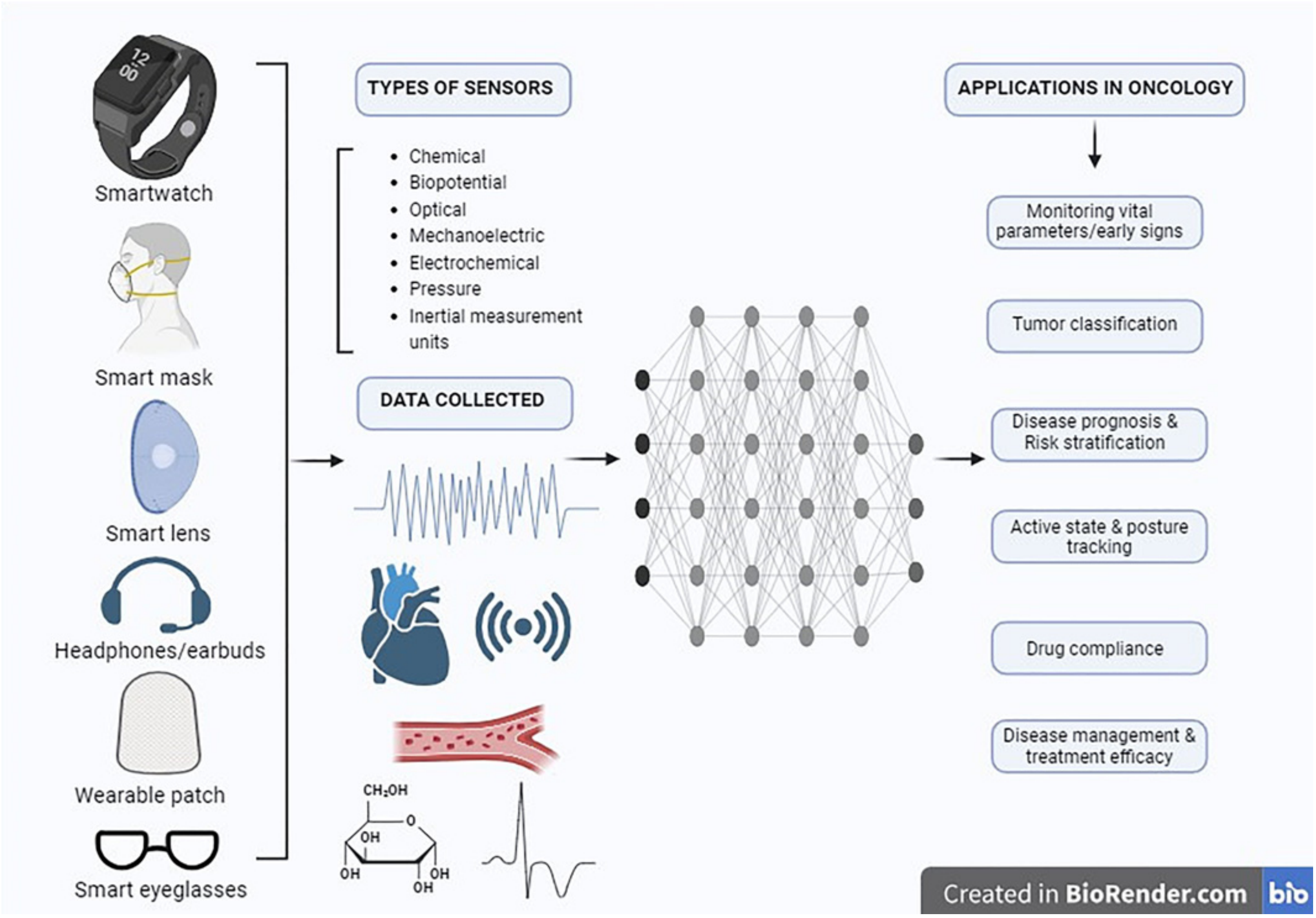

Fig. 1. Schematic diagram illustrating various types of wearables, types of sensors, data collection, and its applications in oncology.

heart rate monitor, and vibration sensor are utilized. Environment patient-compatible sensing can be monitored by altimeter and ambient light sensor [7]. A 3-axis gyroscope can track orientation, while a capacitive sensor can also detect skin electrical conductivity and electromyography [8]. Other types of sensors include microfluidic sensor, nanomaterial-based patch, iontophoretic patch, inertial measurement units, chemical sensors, optical sensors, and biopotential sensors. The sensor positioning allows data collection which is followed by feature extraction and further quantification [9, 10] (Fig. 1).

Types of Data That Can Be Collected Using Wearable Technology

The use of this technology allows the collection of thousands of data points which allows regular monitoring, early detection, and data-driven informed decisions. It allows clinicians to obtain a continuous follow-up of data to further gain insights into the patient's health status and discern patterns over time [11]. Features are derived from signals, captured by various types of sensors as discussed above, to develop a model for classifying or predicting a particular variable. The accuracy of the model typically decreases when adding irrelevant features, emphasizing the importance of domain-specific, expressive features for optimal performance. Certain applications focus on long-term changes, while others concentrate on transient changes triggered by specific events like fall detection and emotion recognition [12].

While the type of data collected using wearables is highly variable, it majorly aids in tracking of motion, activity, biophysical parameter detection, gait altitude, sweat electrodes, biomarker detection, fluoride, pH levels, fall detection, etc. [13] Most of the data collected by wearables is accelerometer-derived data, which includes physical activity, sleep activity, temperature, heart rate, etc. In combination with gyroscopes and magnetometers, accelerometers are integrated into a single unit referred to as an inertial motion unit [14].

Blood pressure, oxygen saturation, heart rate, and respiratory rate are among the most common physiological signs acquired. Other data types include galvanic skin resistance, glucometer, electromyography, electroencephalography, blood pressure, and electrocardiography. Such sensor data types can further aid in real-time monitoring of various events like pathological cardiac events, ECG signal and emergency warning, insulin injection system, fatigue level, stress level, breathing anomaly, and overall patient health status [15].

Data on vital signs collected from wearables can predict numerous clinical laboratory measurements with better accuracy than predictions made using conventional clinically obtained means. The duration of vital signs monitoring and its proximity to the date of prediction play an essential role in the effectiveness of machine learning models [16]. The raw and processed data from wearables can thus render actionable clinical information to clinicians that can assist them with risk of disease evaluation, diagnosis, and treatment management. Moreover, these data can be processed to generate tailored, real-time, and adaptable health coaching interventions as per patient needs. Such data can be securely stored in personal health clouds or electronic health records (EHR) for advanced data analysis and transfer [17].

Application of AI-Enabled Wearable Technologies in Oncology

AI has extensively contributed to the field of clinical informatics over the past few years due to its ability to provide solutions for complex biomedical problems, including cancer. Although significant AI advancements have been made in recent years, their applicability is yet to be explored in clinical oncology [18]. One potential use case is continuous patient screening using AI-integrated wearable technology. These technologies can provide real-time monitoring of vital signs and other health metrics, allowing for early detection of complications and timely interventions. Additionally, AI can analyze large datasets from wearables to identify patterns and predict patient outcomes, improving the overall management and prognosis of cancer patients. The potential applications could thus be extensive; the following are few examples highlighting its implementations in clinical settings.

Activity Monitoring and Patient Health

Several studies have shown that low activity is associated with worsening of symptoms and can act as an indicator of performance status. A study by Bennet et al. [19], conducted on patients undergoing hematopoietic cell transplant, reported that lower Fitbit steps were correlated with elevated symptoms of pain and poorer physical health. In another prospective study on advanced lung cancer patients, lower step count tracked using wearable devices was associated with depression, dyspnea, and reduced quality of life [20]. By leveraging AI-enabled wearable technologies, healthcare providers can gain valuable insights into patients' physical activity levels and overall health status. This can facilitate timely interventions and personalized treatment plans and monitoring, ultimately improving patient outcomes.

Monitoring Frailty and Chemotherapy Tolerance

Understanding and predicting patient tolerance to chemotherapy is critical in oncology care. Cay et al. [21] evaluated the use of pendant-based wearables for monitoring digital indicators of frailty such as cadence, daily steps, postural transitions, and exhaustion in 27 veteran cancer patients. After combining the wearable data with in-clinic Eastern Cooperative Oncology Group (ECOG) assessments, it was suggested that patients with a higher risk of poor response to chemotherapy could be identified.

Another study by Razjouyan et al. [22] investigated whether remote physical activity monitoring could identify older adults with cognitive frailty, a combination of physical frailty and cognitive impairment. Using a chest-worn sensor, physical activity behaviors, patterns, and nocturnal sleep were monitored for 48 h in 163 participants. The study found that specific metrics, such as sleep duration, activity levels, and step counts, were significant in distinguishing individuals with cognitive frailty. A decision tree classifier used these metrics to identify cognitive frailty with an area under the curve of 0.75, showing high sensitivity but moderate specificity. Cancer patients have different tolerances to chemotherapy; frail patients generally have lower tolerance compared to the active ones. Therefore, an active state can be used as an indicator of general well-being, determining the prescribed dose of chemotherapy to cancer patients. In a study done by Mortazavi et al., assessment for frailty was done utilizing smartwatch data through the application of machine learning algorithms. Similarly, Nemati et al. presented a novel two-level classification algorithm for activity state detection using smartwatch data [23, 24].

These findings suggest that wearable sensors can effectively monitor cognitive frailty remotely, providing valuable data for clinicians to identify at-risk individuals and improve treatment plans, potentially delaying the transition to long-term care for older adults. By identifying patients at

Table 1. Summarized table illustrating completed clinical trials incorporating wearable technology in oncology (Source: clinicaltrial.gov)

Sno.	Identifier	Condition	Intervention	Description	Phase	Sponsor	Outcome measures	U.S. FDA-regulated product	Publications
1	NCT03902834	Non-small cell lung adenocarcinoma	Fitbit	Use of Fitbit and proven behavioral change techniques to precondition patients prior to lung cancer surgery Experimental group: intervention	N/A	St. Joseph's Healthcare Hamilton	Feasibility of move for surgery, rate of compliance >70%	No	N/A
2	NCT02911649	Prostate cancer	Garmin Vivosmart, Fitbit Alta, Polar Loop 2	Devices will display daily activity levels as well as weekly overview Experimental group 1: wearable device only, Group 2: online educational workshop only, Group 3: wearable device + workshop Control group: no intervention	N/A	University Health Network, Toronto	Fatigue, depression, sedentary behavior, adherence, retention rate	N/A	N/A
3	NCT03773380	Lung cancer	Breathe Anew Survivorship Program	Use of an integrated knowledge translation approach Experimental group: feasibility	1	St. Joseph's Healthcare Hamilton	Feasibility of rate of compliance of >70%, accrual rate, patient-reported satisfaction, cost per patient	No	N/A
4	NCT04736576	Breast cancer	Smartphone-based application and wearable device	Observational study to evaluate PRO and physical activity using smartphone-based application and wearable device in Japanese patients with HR+/HER2– advanced breast cancer Group 1: palbociclib plus endocrine therapy Group 2: endocrine monotherapy	N/A	Pfizer	Change in patient-reported outcome, patient treatment satisfaction	No	N/A
5	NCT05417438	Cancer survivors	Smartphone-based application and Fitbit	Continuous monitoring of physical activity (step counts, sleep, heart rate) Group 1: prostate cancer patients Group 2: veterans with prostate cancer	N/A	University of Massachusetts, Worcester	Feasibility of enrollment, physical activity, quality of life, usability	No	N/A

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Table 1 (continued)

Sno.	Identifier	Condition	Intervention	Description	Phase	Sponsor	Outcome measures	U.S. FDA-regulated product	Publications
6	NCT05235594	Cancer	Chronolife™ smart t-shirt/ OncoSmartShirt	Shirt is designed with multiple sensors and electrodes which engender 6 different measurement flows continuously Experimental group: smart T-shirt	N/A	Rigshospitalet, Denmark	Feasibility of using the smart t-shirt, technical feasibility, changes in heart rate, skin temperature, physical activity, thoracic impedance	No	(Steen-Olsen EB et al., 2022) [30]
7	NCT03072966	Breast cancer	Fitbit Charge HR/ Fitbit Alta	Investigation of the efficacy of wearable device as a tool of distress monitoring by tracking physical activity Experimental group: distress screening group	N/A	Asan Medical Center	Efficacy of distress screening of wearable device, prediction model of distress	No	(Jung M et al., 2020) [31], (Chung IY et al., 2019) [32], (Chung 1Y et al., 2019) [33]
8	NCT04480541	Oncology caregivers	Mobile health app (Roadmap 2.0), wearable activity sensor and survey administration	Investigation of use of mobile health technology mediated intervention with a focus on the positive aspects of caregiving Experimental group: Roadmap 2.0 _ Fitbit Charge 3	N/A	University of Michigan Rogel Cancer Center	Login rate, enrollment rate, survey completion rate	No	N/A
9	NCT04914702	Pediatric cancer, febrile neutropenia	Everion®, CORE® (on-skin wearable devices)	On-skin wearable device measuring vital signs Group 1: Everion® only Group 2: CORE® only Group 3: Everion® first, CORE® second Group 4: CORE® first, Everion® second Group 5: Everion® and CORE® simultaneously	N/A	Insel Gruppe AG, University Hospital Bern	Feasibility of continuous recording of core temperature, heart rate (HR), heart rate variability (HRV), respiration rate (RR), cumulative length of time of HR, HRV, and RR	No	N/A
10	NCT04659564	Lymphedema	Dayspring device (a novel wearable advanced compression technology)	Open-label study to clinically assess Dayspring™ to determine if potential barriers to lymphedema self-care were effectively addressed Experimental group: breast cancer-related lymphedema	N/A	Koya Medical, Inc.	Quality of life questionnaire, arm volume maintenance, safety, therapy adherence	Yes	N/A

Table 1 (continued)

Sno.	Identifier	Condition	Intervention	Description	Phase	Sponsor	Outcome measures	U.S. FDA-regulated product	Publications
11	NCT03874754	Cancer survivors with multiple chronic conditions	Tailored Technology-Enhance Home-based exercise program (iHBE)	Monitoring of physical performance, provide immediate feedback, send reminders. Coded raw data from the device sent to servers, stored in the database and custom reports created Experimental group: iHBE program group Control group: Usual care	N/A	Sidney Kimmel Comprehensive Cancer Center at Johns Hopkins	Change in fatigue, resilience, physical and mental well-being, brain-derived neurotrophic factor level (in serum and sweat)	No	N/A
12	NCT02773329	Cancer, chemotherapy-induced peripheral neuropathy	Sensor-based interactive exercise (game-based exercise), intervention without game-based exercise	Interactive game-based balance training (repetitive weight shifting and virtual obstacle crossing tasks), sensors provide real-time visual/auditory feedback from foot and ankle position and allowed perception of motor errors during each motor-action Experimental group: intervention with game-based exercise Control group: intervention without game-based exercise	2	Baylor College of Medicine	Gait speed change, balance change, fear of failing using Fall Efficacy Scale International (FES-I) questionnaire	N/A	N/A
13	NCT03927742	Melanoma	Behavioral: shade wearable device and application with and without UV messaging activated	Investigation of technology-based strategies in melanoma survivors to improve sun exposure and protection behaviors Experimental group: shade and application with UV message activated Control group: shade and application without UV messaging	N/A	University of Minnesota	Sun protection habits index, self-report of sunburn	No	(Vogel RT et al., 2020) [34]

Table 1 (continued)

Sno.	Identifier	Condition	Intervention	Description	Phase	Sponsor	Outcome measures	U.S. FDA-regulated product	Publications
14	NCT04616768	Lung cancer, gastrointestinal cancer	PRO questionnaire, step monitoring, active nudge text feedback, PROStep dashboard (clinicians)	PRO questionnaire will inquire about seven symptoms selected by lung and GI oncology clinicians, step monitoring will send step data to the research team, active nudge text feedback describing worsening of symptoms Experimental group: arm B (intervention without text feedback), arm C (intervention with feedback) Control group: no intervention	3	Abramson Cancer Center at Penn Medicine	Patient perceptions of symptom management, adherence, Fitbit step data, comparison of PRO (patient-reported outcome) scores	No	(Parikh RB et al., 2022) [35]
15	NCT04751162	Non-small cell lung cancer	Actigraphy device (wearable) and mobile application	Focuses on examining perceived technology usability in a limited sample of participants and feasibility of translating the actigraph data into performance status scores using a quantitative-qualitative approach Experimental group: lung cancer patients equipped with actigraphy device and mobile app	N/A	Hoffmann-La Roche	ECOG-PS assessment, usability, sensitivity to changes in ECOG-PS	N/A	N/A
16	NCT03315286	Skin cancer, actinic keratoses (AK)	Device: shade ultraviolet sensor	Randomized partially blinded study with recent history of AK lesions and evaluate incidence of new AKs after one summer Experimental group: shade ultraviolet sensor Control group: standard of care counseling	N/A	Weill Medical College of Cornell University	Quantification of Actinic Keratosis and non-melanoma skin cancer Using the UV Sensor versus Control Group, impact of UV sensor on patient's quality of life, quantification of melanoma skin cancers, squamous cell carcinoma, basal cell carcinoma, Assessment of cyclobutane pyrimidine dimers in sun damaged skin and sun protected skin after using the UV sensor versus control group	Yes	N/A

Table 1 (continued)

Sno.	Identifier	Condition	Intervention	Description	Phase	Sponsor	Outcome measures	U.S. FDA-regulated product	Publications
17	NCT04827446	Breast cancer, prostate cancer, patients who have undergone autologous hematopoietic stem cell transplant (HSCT)	Wearable sensor, blue-blocking glasses, clear glasses	To assess how lighting interventions distributed via mobile app affect fatigue, sleep, and quality of life across three populations of cancer patients, randomized 1:1 either to SYNC app or to a control group Experimental group: light intervention through SYNC app + blue-light blocking glasses Control group: placebo light intervention via SYNC app + clear glasses	N/A	University of Michigan Rogel Cancer Center	Change in fatigue, level of sleep disturbance, anxiety, depression, physical function, overall health metrics	No	N/A
18	NCT03612596	Breast cancer	Behavioral: narrative visualization, standard self-regulation	A pilot study to iteratively test scrapbook materials which targets integrated regulation, participants use narrative visualization to connect their step data to events/feelings and reflect on their behavior Experimental group: narrative visualization Control group: standard self-regulation	N/A	The University of Texas Medical Branch, Galveston	Step count, intrinsic and integrated regulation, exercise identity, basic psychological needs, quality of life	No	N/A
19	NCT04259905	Breast cancer	Active video game teleconference support group, pedometer, standard support group	12-week physical activity intervention (Pink Warrior) on randomized participants Experimental group: active video game teleconference support group Control group: standard support care + pedometer	N/A	The University of Texas Medical Branch, Galveston	Walking physical activity, quality of life, hand grip strength, self-regulation, psychological feelings, fatigue, dietary plan, adherence, attrition	No	N/A
20	NCT04144127	Prostate cancer	Garmin Vivofit wearable device: soccer specific	Participants will be offered an intensive intervention including RS programming and lifestyle education Experimental group: Soccer group	N/A	Emory University	Lumbar spine bone mineral density (BMD), total hip BMD, osteocalcin level, C-terminal telopeptide of collagen, weight, BMI, HR, blood pressure, lean body mass, body fat percentage, aerobic capacity, dietary intake, sleeping and alcohol habits	No	N/A

risk of poor chemotherapy response early on, clinicians can tailor treatment plans more effectively. As this technology continues to advance, its integration in oncology could become a standard practice, offering a more nuanced and dynamic approach to patient care.

Biomarker Detection and Tumor Monitoring

Advances in wearable technology are revolutionizing the way biomarkers are detected and tumors are monitored in oncology. These innovations enable continuous, real-time health monitoring, offering significant improvements in decision-making and plan of action.

For instance, C-reactive protein is an essential biomarker in medicine and is often used to test inflammation in the body. The quantification of protein biomarkers in blood is a time-consuming process that requires professional assistance. A wireless and wearable patch was designed by Tu et al. [25] for real-time electrochemical detection of C-reactive protein in sweat. It incorporates iontophoretic sweat extraction, microfluidic channels for sampling, and a graphene-based sensor for quantification. Such tests could be incorporated in cancer patients to provide valuable clinical information for assessing prognosis, treatment response, and risk of complications. Another study by Siboro et al. [26] utilizes a thermoplastic polyurethane film embedded with hafnium oxide nanoparticles to enable dynamic monitoring of tumor regression and growth. The film serves as a dielectric elastomer strain sensor and influences the electrical impedance by undergoing proportional deformation with changes in tumor volume. This is efficacious for designing accurate treatment plans, dosing for smaller tumors, and investigating treatment effectiveness at larger volumes. This wearable strain sensor exhibits notable accuracy even in the case of minute volumes with a significantly lower error percentage.

Treatment Management and Adherence Monitoring

Apart from detection purposes, AI-enabled wearable devices can also help in treatment management by tracking adherence to medication and a healthy diet [27, 28]. In the case of breast cancer, a healthy diet post-diagnosis can decrease the risk of mortality, whereas adherence to a Western diet has been found to increase the risk of overall mortality [28]. Resende e Silva et al. [29] developed a framework of mobile applications and wearable devices for diet management. It employs machine learning and deep learning models for food recognition and assessment, enabling dietary intervention using food images and physical activity data from wearable devices. Weeks et al. developed a wearable sensing system to track medication adherence and physiological signals of patients [27, 29]. These studies suggest the utility of AI-enabled wearable devices in monitoring adherence to medication and a healthy diet of cancer patients for better clinical outcomes.

According to clinicaltrial.gov, to date, there have been 21 completed clinical trials utilizing this technology in oncology, summarized in Table 1. Moreover, 27 studies are currently recruiting and 6 are ongoing. Table 2 summarizes the studies that have utilized AI tools and wearables in oncology.

From Bedside to Bench and Vice Versa: Challenges in Implementation

Wearable devices generate a tremendous amount of data from continuous monitoring of physiological biomarkers. Therefore, storage, preprocessing, and integration of these data must be done to produce high-quality data for AI applications [43]. Additional issues like data security and privacy need to be addressed to facilitate regulated sharing and usage of these data [44]. Physiological signals captured by wearables are highly susceptible to motion distortions and outside noise, which should be mitigated before [45].

While building AI models, biased data can lead to non-favorable decision-making toward certain groups of patients. This can influence the robustness of the models among diverse groups of patients in different clinical setups [44, 46]. Cancer care is multidisciplinary since it is associated with a widespread array of comorbidities, each with a complex and unique pattern of care, and it often becomes challenging to cater to each condition with a single approach. Ethical values are subjective, and while AI systems offer potential, their accuracy and accountability pose several challenges. Emerging therapeutic techniques face hurdles in message delivery and operational consistency, affecting patient enrollment in clinical research. Integration of oncology practices aims to streamline workflows and improve data utilization, but systems-level fragmentation may hinder rapid change implementation [47]. There is also a need of rigorous testing of such devices and models along with standardization and calibration of sensors for enhanced accuracy and sensitivity.

Future Perspectives

Utilizing wearable technology will usher in a new era of managing, utilizing, and standardizing data. It will enable hospitals and insurance companies to subsidize wearable costs, ultimately reducing downstream medical expenses

Table 2. Summary of studies incorporating AI tools and wearables in oncology

Authors	Dataset	AI technology	AI task	Reported outcome	Reference
Liu et al. [36] (2023)	Smartwatch data (40 patients)	Supervised machine learning	Mortality prediction in end-of-life care cancer patients	96% AUROC, 93% accuracy	Liu et al. [36] (2023)
Torrente et al. [37] (2022)	Wearables data (350 patients) and clinical data (5,275 patients)	Multiple layer neural network	Cancer prognosis, risk stratification and follow-up management	Constructed risk profile	Torrente et al. [37] (2022)
S et al. [38] (2020)	Wearable patch data (201 subjects)	AI-enabled predictive model	Classify benign and malignant breast lesions	78% accuracy	S et al. [38] (2020)
e Silva et al. [39] (2018)	Food image and Fitbit data	Computer vision and machine learning	Diet monitoring	87.2% accuracy	e Silva et al. [39] (2018)
Weeks et al. [40] (2018)	Wearable patch data (14 subjects)	Machine learning	Medication adherence	98% accuracy	Weeks et al. [40] (2018)
Nemati et al. [41] (2017)	Smartwatch data (20 subjects)	Novel two-level classification algorithm	Activity state	95.6% accuracy	Nemati et al. [41] (2017)
Mortazavi et al. [42] (2015)	Smartwatch data (20 subjects)	Support vector machine (SVM) model	Posture tracking	F1 Score of 93%	Mortazavi et al. [42] (2015)

for consumers. Moreover, it will lead to the widespread adoption of personalized medicine in diagnostic procedures. Wearable technology has the potential to accelerate the shift toward personalized medical treatment. These devices are easily adaptable and can conform to individual patient needs. Wearables are becoming increasingly affordable and accessible worldwide, making them an ideal solution for enhancing patient care in oncology [8].

Additionally, there are several unexplored areas utilizing the above technologies that could be converged in daily clinical practices. For instance, since circadian clock plays a critical role in cancer, the incorporation of chronotherapeutics (i.e., administrating treatment at specific time in accordance with body's circadian clock) into oncology decision-making represents a groundbreaking avenue for leveraging wearable device technology. By harnessing wearable devices to track the circadian clock, we can delve into the intricate dynamics of tumor progression [48, 49].

This could aim to explore how circadian rhythms influence critical mechanisms such as cell cycle regulation, repair mechanisms, and the modulation of immune cells in tumor surveillance. Furthermore, the role of circadian rhythms in metabolic regulation and hormonal factors like melatonin, known for its negative regulation of angiogenesis and cell proliferation, could be further studied. Further research is required to warrant the development of targeted chronotherapeutic interventions tailored to the individual circadian rhythms of cancer patients, thereby optimizing treatment efficacy and patient outcomes [50]. Other areas that may require further exploration include tumor microenvironment sensing and gut microbiome analysis. Certain microbial population can affect the efficacy of chemotherapy, immunotherapy and can also impact the metabolic pathways of several drugs. Specific microbial species and their toxic proteins often promote tumor progression by inducing gene instability, while alterations in intestinal microecology or heightened microbial presence in the tumor microenvironment can hinder antitumor immunity [51].

Overall, AI is a burgeoning and rapidly progressing paradigm that spans various scientific domains, including decision-making in oncology. It is transforming the current landscape by integrating different datasets with recent developments in high-performance computing and innovative deep learning techniques. Remarkably, the applications of AI are growing to entail novel methods for cancer detection, screening, diagnosis, and categorization. Moreover, its utilization is expanding in understanding cancer genomics, studying tumor microenvironments, evaluating prognostic and predictive biomarkers, and developing approaches for follow-up care and drug discovery [52].

Conclusion

The amalgamation of wearable device technology and AI represents a promising frontier in oncology, offering novel avenues for personalized patient care and research innovation. Through continuous monitoring and AI-driven analysis, wearable devices empower clinicians to make data-driven decisions, optimize treatment strategies, and improve patient outcomes. While challenges such as data management, privacy concerns, and regulatory hurdles persist, ongoing research and collaboration hold the potential to overcome these barriers and unlock the full potential of wearable devices in oncology. As we navigate this evolving landscape, it is imperative to prioritize ethical considerations, promote data transparency, and foster interdisciplinary collaboration to realize the transformative impact of wearable devices and AI in cancer care.

Conflict of Interest Statement

The authors have no conflicts of interest to declare.

Funding Sources

This review was not supported by any sponsor or funder.

Author Contributions

P.S.M. and I.G. conceptualized and finalized the article. M.B. and R. wrote the manuscript and provided substantial inputs. P.S.M., I.G., and P.G.R. provided significant insights and feedback. All authors gave final approval for publication.

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