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Review

Digital Health Applications in Oncology: An Opportunity to Seize

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REVIEW

Abstract

Digital health advances have transformed many clinical areas including psychiatric and cardiovascular care. However, digital health innovation is relatively nascent in cancer care, which represents the fastest growing area of health-care spending. Opportunities for digital health innovation in oncology include patient-facing technologies that improve patient experience, safety, and patient-clinician interactions; clinician-facing technologies that improve their ability to diagnose pathology and predict adverse events; and quality of care and research infrastructure to improve clinical workflows, documentation, decision support, and clinical trial monitoring. The COVID-19 pandemic and associated shifts of care to the home and community dramatically accelerated the integration of digital health technologies into virtually every aspect of oncology care. However, the pandemic has also exposed potential flaws in the digital health ecosystem, namely in clinical integration strategies; data access, quality, and security; and regulatory oversight and reimbursement for digital health technologies. Stemming from the proceedings of a 2020 workshop convened by the National Cancer Policy Forum of the National Academies of Sciences, Engineering, and Medicine, this article summarizes the current state of digital health technologies in medical practice and strategies to improve clinical utility and integration. These recommendations, with calls to action for clinicians, health systems, technology innovators, and policy makers, will facilitate efficient yet safe integration of digital health technologies into cancer care.

Mr Brown and Mr Jones are 2 males who underwent chemoradiation with high-dose cisplatin for locally advanced head and neck cancer. Mr Brown was treated in the early 2000s. He experienced substantialnausea and dehydration after his first dose of cisplatin, resulting in an emergency department visit for intravenous fluids. Toward the end of his 6-week radiation course, he had lost approximately 40 pounds. He eventually required a feeding tube and had persistent difficulty swallowing even several months after his course ended.

Mr Jones was treated in 2019. Prior to this therapy, he enrolled in a text-based patient-reported outcomes (PRO) reporting program. He and his family caregiver were sent daily symptom surveys based on the PROs version of the Common Terminology Criteria for Adverse Events (1) and reported decreased oral intake during the first week of cisplatin. This information was automatically fed into the electronic health record (EHR). His oncology care team responded by ordering regular intravenous (IV) fluid infusions in the outpatient and home settings, avoiding an emergency department visit. Despite living nearly an hour from his oncology clinic, his oncology team had twice-weekly video appointments via a secure telemedicine platform and recorded his weight using a wireless scale. Owing to early reporting of his appetite loss and nausea, he was referred for palliative care and nutrition consultation early in the course of his radiation and did not require a feeding tube.

The vastly different experiences of these 2 patients demonstrate the potential for digital health innovations to shape the

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oncology patient care experience. Digital health encompasses health content, interventions, and applications such as communication and remote monitoring tools to improve and personalize care delivery and enhance patient quality of life (2). The COVID-19 pandemic presented an unprecedented opportunity to accelerate integration of digital health technologies to increase the likelihood that patients would receive high-quality cancer care outside of the clinic or hospital (3). These opportunities are most salient in patient- and family-facing solutions that include access to health records, symptom management, and telemedicine visits; clinician-facing decision and diagnostic support; and dissemination of clinical trials into the community. Data standardization, privacy and security, and adequate reimbursement models remain persistent barriers to the advancement of digital health infrastructure in oncology.

Based on proceedings of a 2020 workshop convened by the National Cancer Policy Forum of the National Academies of Sciences, Engineering, and Medicine (4), we characterize the current state of digital health applications in oncology practice and research, highlight barriers to further implementation, and offer strategies to improve equitable use of digital health technologies to maximally improve outcomes for patients with cancer.

The Current State of the Digital Health Ecosystem in Cancer Care

Worldwide, the market for digital health is expected to grow from US$84 billion in 2019 to US$221 billion by 2026—a 14.8% annual growth rate (5). This growth will be particularly notable in cancer care, the fastest growing area of US health-care spending, where cancer-attributable cost for medical services and prescription drugs will reach US$246 billion by 2030 (6). Owing to the vast potential for digital health technologies to improve quality and reduce spending in cancer care, a 2020 National Cancer Policy Forum workshop convened leadership from oncology physician and nursing societies, cancer care practitioners, researchers, payers, policy makers, entrepreneurs, EHRs vendors, and patient and caregiver advocates to discuss opportunities for digital health in cancer care. Panelists discussed 3 areas of opportunity in digital health with emerging successes in cancer care (Box 1).

Patient-Generated Health Data

Patients with cancer often face substantial symptoms from their cancer, adverse effects from cancer-associated therapy, and declines in functional status and quality of life due to cancer progression or treatment (7-13). Identifying patients with high symptom burden, poor quality of life, or poor functional status is thus critical to ensure high-quality care for patients with advanced cancer (14-16). However, conventional clinician-led symptom monitoring can lead to underreporting of patients' symptoms because of frequency of visits, limited time in the clinical visit, communication challenges, and human psychology (17). In large prospective studies, oncology clinicians assess patient symptom burden only 40% of the time. Furthermore, in nearly three-quarters of cases where patient- and clinician-reported symptoms are not concordant, clinicians underestimate symptom severity (18-21).

Patient-generated health data are routinely collected information about symptoms and activity levels that patients either report directly or passively record using devices such as wearable accelerometers (21-23). Patient-facing digital technologies can be grouped into 2 categories: technologies to improve symptom and disease management and remote patient monitoring.

Emerging evidence supports the collection of PROs—health outcomes that are directly reported by a patient (24-27). Routine PRO assessment in oncology care can reliably improve symptom management, resulting in improvements in health-care utilization, quality of life, and even patient survival compared with standard clinical assessment based on imaging (28). PROs may be collected in the clinic, on paper, or via digital applications that link to the electronic medical record, with early trials suggesting high levels of adherence at nearly 80% for weekly and monthly PRO questionnaires among oncology patients (29, 30). However, limiting PRO collection to in-clinic visits in oncology may be too infrequent to comprehensively account for patients' symptom burden (31-33). Technologies that enable remote PRO collection using questionnaires delivered via mobile phone applications may provide more granular information about symptom burden to clinicians (26). Artificial intelligence (AI)–enabled "conversational agents"—systems that mimic human conversation using text or spoken language—may allow for automated responses to PROs, enabling more timely symptom management and counseling regarding medication adherence without the need to wait for a clinician response. Early evidence suggests that text-based conversational agents in oncology are usable and acceptable to patients and improve oral therapy medication adherence (34). Family caregivers may use similar reporting mechanisms to report their loved ones' symptoms or to even report caregiver distress or burden (35).

Remote monitoring technology includes wearable and mobile technologies that collect health information from patients in the community or home setting. The data collected require minimal clinician involvement or manual data entry. Physiologic variables of relevance that can be collected via remote monitoring technology include activity levels and step counts, sleep, and blood pressure (36). In particular, passive activity monitoring via accelerometer-measured step counts may provide objective measures of functional status that can be trended over time to inform discussions about treatment and prognosis. Activity monitoring among patients with cancer is feasible and associated with high levels of adherence in prior trials (37-40). In prospective and randomized trials, passively collected physical activity monitoring was associated with reduced hospitalizations, fewer adverse events, and even improved survival (41). Similar remote monitoring devices can automatically detect adherence to complex oral chemotherapy regimens and may be used to facilitate early adherence efforts prior to consequences such as disease progression (42). Additionally, remote monitoring can include frequent assessment of PROs to facilitate the early identification of adverse treatment consequences or other health issues (43).

Diagnostic and Predictive Analytics

Amid growing participation by oncology clinicians in value-based payment programs and care models, there is an increasing desire to improve diagnostic and risk stratification methods in oncology to tailor care based on formal risk. Increasing availability of high-dimensional data from the EHR enables improved risk stratification. Two trends in diagnostic and predictive analytics serve as promising examples of clinician-

Box 1. Selected domains of digital applications and cancer care and research

Patient-facing applications

- Patient portal optimization
- Coherent sharing of clinical data for patients
- Patient-clinician applications
  - Data exchange between patients and clinicians
  - Patient-reported outcomes
  - Remote monitoring (activity levels, weight tracking, etc)
  - Use of telemedicine to facilitate care and reduce travel burden on patients (standard of care and clinical trials)

Diagnostic and predictive analytics

- Artificial intelligence–based diagnostic analytics to identify patterns in radiology or pathology images
- Predictive analytics to stratify patients by mortality, hospitalization, or other adverse outcome risk

Workflow optimization and research

- Natural language processing to capture clinically relevant data to improve documentation and workflow
- Increased use of structured data to better support clinical decision support and research
- Automated decision support to support real-time decision making
- Platforms for curation and aggregation of real-world data to better assess quality and care patterns and assess real-world treatment effectiveness and patient experience
- Early adverse event detection via remote monitoring in clinical trials

facing technologies that can improve the accuracy and efficiency of oncology care.

First, rapidly advancing AI–based analytics in fields like radiology and pathology hold promise for augmenting diagnostic acumen in oncology, as well as improving efficiency and work volume per professional. There is considerable heterogeneity in pathology reads of bronchoscopic biopsies for non-small cell lung cancer detection and prostate biopsies for Gleason score determination (44,45). Similar heterogeneity in radiology diagnosis also exists in mammography and computed tomography reads for cancer, albeit to a lower scale (usually $<$10% variability) (46,47). Digital images of pathology slides can be used to develop machine learning (ML) algorithms to detect and grade cancers and to help pathologists reach a diagnosis. AI algorithms can detect metastatic breast cancer from images of sentinel lymph node biopsies with high discrimination (area under the receiving operator characteristic curve = 0.99) comparable to pathologists' interpretations (48). These models allow for improved ability to scan large tissue sections to identify cancer cells and may help improve the workflow of pathologists by allowing them to dedicate more time to other tasks. Similarly, in the field of radiomics, computer-aided detection has applications in detecting important variables related to staging, including cancerous lung nodules on computed tomography or prostate lesions on magnetic resonance imaging. For example, preoperative identification of lymph node status via imaging could reduce the need for surgical interventions and help determine whether there is extranodal extension of the cancer cells, potentially informing the need for adjuvant treatment escalation (49).

Second, predictive analytics can also be used for clinical and population health risk stratification to direct important resources to patients to avoid downstream outcomes. For example, ML-based predictive algorithms based on the EHR can identify patients at risk for mortality or acute care use among patients receiving chemotherapy, with oftentimes greater accuracy than clinicians' intuition (50,51). This prediction could be used to influence clinician decision making along the cancer spectrum, such as after chemotherapy, after colorectal cancer surgery, or in discharge planning. Such ML-based predictive algorithms may be used to "nudge" clinicians toward value-based care streams for high-risk patients or to default patients into population health management programs to improve advance care planning and/or reduce unplanned utilization (52,53).

Workflow Optimization and Research

Enhancing the inclusion of certain structured data elements in the EHR could greatly improve the ability to display critical clinical data to clinicians and care coordinators at the time of care. In oncology practice, many data elements needed to understand the patient journey are documented in unstructured documents, such as physician notes and diagnostic reports. Extracting this data for the purpose of transitioning care or coordinating between institutions often requires many hours of clinicians' and care coordinators' time—time that could be spent with patients. Even when data fields that permit structured data entry are present in the EHR, such as stage and performance status, missing data are common. AI methods such as natural language processing and ML are increasingly applied in the research setting and in support of patient care and may aid in the extraction of important pathologic (eg, Gleason score), radiologic (eg, radiologist interpretation of progression), and cancer-specific (eg, performance status) covariates that are documented in consistent ways in structured text (54-56). Even with improved technology, natural language processing has a substantial error rate, and improving the capture and completeness of specific data in structured form should be encouraged and incentivized for clinicians who are entering clinical data and the EHR vendors who build the data capture tools to support clinician documentation and workflow. Gathering and optimally displaying critical data could not only facilitate more efficient care but also support safer care and more robust decision support tools, if implemented in a way that does not add to administrative burden for the clinician and their workflow. Stakeholder interviews with end-user clinicians and health workers, possibly with consultation of implementation and human factors scientists, could help with administrative simplification and careful implementation of these tools. Furthermore,

if critical data elements were present in structured format in the EHR, live-time data could assess quality of care and inform care improvement efforts. Archival structured data could also improve understanding of patient-specific factors such as tolerance of treatment and quality of life in real-world settings.

Increasingly, digital health applications can be used to support clinical research and quality improvement efforts. The number of clinical trials that include a digital health device as part of the intervention has increased from 8 in 2000 to at least 1177 in 2018—a 34.8% compound annual growth rate. Furthermore, PRO and remote health monitoring may be used to detect adverse events as well as safety concerns earlier in the course of the trial, which could prompt immediate quality improvement actions (53). This would substantially decrease the workload of research coordinators, who spend considerable time per patient documenting this information. AI algorithms may also be used to match patients with clinical trials (57,58).

COVID-19 and the Opportunity for Digital Health

The COVID-19 pandemic has had 3 major impacts in accelerating integration of these and other digital health technologies into oncology practice.

Telemedicine

The COVID-19 pandemic and associated stay-at-home orders forced oncology practices to decrease face-to-face visits and scans. Instead, practices rapidly pivoted toward virtual patient interactions. At some institutions, during the first 3 months of the pandemic, nearly three-quarters of all oncology visits were video or telephone visits (59). This was enabled by the Centers for Medicare and Medicaid Services relaxing geographic and patient eligibility barriers for telemedicine, Health and Human Services allowing preexisting audiovisual platforms (eg, Zoom Video Communications, BlueJeans) to be repurposed for healthcare utilization, and Centers for Medicare and Medicaid Services and other payers reimbursing telemedicine at values commensurate to in-person visits (60).

Digital Therapeutics

Remote monitoring platforms grew exponentially during the pandemic, given the need to decrease face-to-face visits and subsequent exposure risk for patients with active cancer undergoing treatment (37-40) or postsurgery. In particular, given the potential for rapid deterioration due to COVID-19 among patients with cancer, text monitoring platforms and passive vital sign monitors were deemed feasible and led to improved identification of high-risk patients (61). Remote monitoring tools such as remote PROs and biosensors fed to the care team enabled quicker triage.

Clinical Trial Infrastructure

A key lesson of the pandemic was that the Food and Drug Administration (FDA) was enabled to deliver rapid advice and review of drugs, vaccines, and digital therapeutics. The FDA released guidance encouraging telemedicine use in clinical trials. Furthermore, the FDA allowed for expanded use of noninvasive devices, such as spirometers and blood pressure monitors, after the pandemic. Clinical trials have increasingly relied on digital mechanisms to advertise and recruit patients. Moreover, virtual collection of registries and rapid data sharing enabled COVID-related registries that were essential to generating high-quality evidence in the early phase of the pandemic.

Barriers to Implementation

Despite current successes in digital health deployment in oncology, there remain several potential barriers to broad deployment of digital health tools. First, there are important differences among patients in digital health literacy and access to necessary tools such as broadband. Lack of digital health literacy may preclude engagement with even the most effective digital health tool (62). This poses a major health equity risk—lack of digital health literacy may reinforce and widen existing disparities in cancer care. Second, PROs and digital health tools face reimbursement challenges, and oftentimes such tools are either covered through small-scale health system pilots or are paid for patients (63,64). Third, emerging evidence suggests that AI and ML tools can be biased as a result of their training datasets, systematically underestimating risk among racial and ethnic minorities and underrepresented subgroups (65,66). This may result in suboptimal deployment of care management and other resources for high-risk patients in minority subgroups. Fourth, sophisticated algorithms or digital health tools that only result in additional alerts or emails to clinicians will not succeed. Attention to implementation factors that seamlessly integrate or simplify clinician workflows is critical.

Opportunities Moving Forward

The workshop developed a series of policy recommendations (see Box 2) to improve access to and utility of digital health technologies in cancer care.

EHR Data Standardization and Interoperability

Utilizing EHR data to devise decision support and quality improvement interventions holds promise. As an example, good care coordination over transitions of care and navigating the initial cancer diagnosis is critical to prevent duplicative or missed care. Having quick access to oncology EHRs would improve workflows of care coordinators and patient navigators and ensure more timely care. However, a barrier to good care coordination, along with other aspects of oncology care, is a lack of interoperability and standardization of EHRs, as well as tools to aid clinicians in documentation with structured data. In addition, the frequent absence of structured data in pathology and radiology reports remains an impediment to advances. Since the Office of the National Coordinator for Health Information Technology first began tracking interoperability in 2014, the proportion of hospitals that use a national network to query patient information increased from 20% to 55% in 2019—a promising trend (67). However, as of 2015, less than 30% of hospitals adhered to all 4 aspects of interoperability: finding, sending, receiving, and integrating electronic patient information from outside providers (68). Furthermore, in the precision oncology era, standard EHR elements that are included in data sharing often do not contain molecular characteristics of the tumor, dosing for chemotherapy and radiation, and clinical trial data that are key to care for the 21st-century patient with cancer. Thus, many oncology clinicians and researchers rely on antiquated methods, including fax machines,

Box 2. Recommendations for action to ensure successful integration of digital health technology in cancer care

Data standardization and interoperability

- Federal and state government
  - Endorse consensus data standards for clinical data in oncology (eg, Minimal Common Oncology Data Elements) as a requirement across electronic health record (EHR) vendors
  - Require Fast Healthcare Interoperability Resource application programming interface (API) adoption from all certified EHR vendors
- Private industry
  - Develop natural language processing algorithms to extract more robust clinical data (eg, stage, performance status) from unstructured notes to streamline clinical care and clinical research
  - Develop tools that drive facile collection of critical structured data elements by clinicians in EHRs
- Health systems
  - Establish financial and nonfinancial strategies to incentivize clinician adoption of patient-reported outcomes (PROs) and utilization of standardized structured data
  - Integrate fast healthcare interoperability resources (FHIR) APIs into institutional EHRs to adhere to federal Office of the National Coordinator for Health Information Technology interoperability requirements

Control and security of digital data

- Federal and state government
  - Establish rules for email and app-based information sharing outside of patient portals
- Private industry
  - Develop artificial intelligence–based programs that securely collect, organize, integrate, and share digital health data, even data from unstructured notes and radiology and pathology reports
- Health systems
  - Develop data sharing mechanisms that offer complete patient access to health data in patient-friendly language that respects different levels of health literacy.

Reimbursement of digital health technologies

- Federal and state government
  - Develop policies or demonstration programs to reimburse expenses related to electronic PRO implementation and maintenance
  - Incorporate PROs as a performance evaluation measure used to adjust payment in alternative payment models
- Health systems and private industry
  - Generate high-quality evidence that further demonstrates the economic value of broad-based electronic patient-reported outcome capture and other digital health technologies

Bias mitigation and promoting equity

- Federal and state government
  - Integrate standards for representative training sets and testing solutions in underrepresented and/or marginalized populations into regulatory standards for digital health tools
- Private industry
  - Develop analytic techniques for auditing bias in proprietary algorithms
  - Ensure that patient-facing digital health tools are accessible to non–English-speaking individuals
- Health systems
  - Ensure that digital health web- or app-based tools are available at community oncology centers, not only urban academic hubs
  - Validate digital health technologies for use in diverse populations

to share and receive information. Novel digitization strategies for this critical data are necessary to create a "digital highway" for oncology data (69). Additionally, Fast Healthcare Interoperability Resource–based federated data platforms in countries such as Germany have shown success in securely sharing secondary patient data for translational clinical research in oncology, ensuring broader scale to traditionally siloed translational oncology research (70). Of note, the Office of the National Coordinator for Health Information Technology issued a rule that Fast Healthcare Interoperability Resource application programming interfaces will be required from all certified EHRs in the United States by the end of 2022 (71). Finally, patient-driven data sharing platforms such as Ciitizen (72) and AliveAndKickn (73) are particularly promising in bringing together important clinical data in relatively rare conditions such as cholangiocarcinoma and Lynch syndrome, respectively, to offer researchers access to large data sets and match patients with relevant clinical trials.

Even with interoperable records, there are many inconsistencies in the way that data are captured in the EHR. For example, data on patient tobacco use are recorded differently across EHRs, and PROs are often captured using different templates and nomenclatures—if they are captured at all (74). The advent of ontologies such as Minimal Common Oncology Data Elements (mCODE) (75) can ensure data standards across EHRs to improve clinical care

and research. mCODE creates a consensus data standard to facilitate patient data transmission across health settings. The first version of mCODE had 73 data elements, including data on demographics, cancer type, and genomics (76). Future iterations should consider including other data, including PROs and traditional clinical trial eligibility criteria, to streamline clinical care and research. Such standardized tools may free oncology clinicians from low-value and repetitive coding and data entry, allowing greater time for patient care and decision making. Health systems are encouraged to develop financial and nonfinancial incentives to utilize standardized tools as part of their routine workflow and documentation.

Bias mitigation and equitable representation go part and parcel with data standardization efforts. Representation of racial and ethnic and socioeconomically disadvantaged populations, whether in algorithm training sets or cohorts for pilot testing or clinical trials, is highly inconsistent and currently inadequate overall. Federal and state governments and other regulatory bodies should integrate standards for representative training sets and testing solutions in underserved and marginalized populations into regulatory standards for digital health tools. Relatedly, health systems should validate digital health technologies for use in diverse populations, including racial and ethnic minorities, rural-dwelling populations, and others facing socioeconomic disadvantage.

Standardized critical oncology-related data would not only strengthen decision support tools but also could be used for rapid assessment of quality of care and patient outcomes. The ability to interrogate cohorts of patients in real time for effects of a variety of factors, such as COVID-19 infection, effects of treatment, would facilitate rapid understanding of clinical scenarios. The inability to do this currently was evident in the early stages of the COVID-19 pandemic when we had little information to help us understand effects of the infection and optimal strategies for our patients. In addition, a better understanding of how real-world patients are affected by disease and the treatments we utilize would be greatly enhanced with more robust structured data widely used in EHRs.

Patient Control and Security of Digital Data

Even as digital health technologies have allowed more patient data elements to be collected, a challenge is that patients have access to view only a fraction of this data. Nearly 100% of patients with cancer wish to have access to clinical notes (77). In April 2021, the 21st Century Cures Act Interoperability and Information Blocking Rule formally went into effect, penalizing health-care organizations, certified EHR vendors, and health information networks and exchanges that interfere with sharing electronic health information for any purpose where such sharing is permitted by law, including with the patient. Historically, there are important limitations to the types of data patients can view on these portals. New EHR certification standards and the Information Blocking Rule are shifting this dynamic, and patients are increasingly able to access and download clinical notes online.

There is an immediate need for programs that increase patient access to data by securely collecting, organizing, integrating, and sharing digital health data beyond EHR data, including imaging results, genomic data, functional status scores, and other documentation. AI-based tools can self-learn to extract relevant data elements from vast amounts of unstructured data for patient sharing purposes and are thus essential; this information could also be used to reduce friction in information sharing and gathering in transitions between institutions. However, given the critical importance of accuracy in health-care applications, special attention to context-specific reliability, validation, and interpretability of machine-derived information is essential. Second, international governance policies and standards can enable clinicians, care coordinators, and researchers to use data safely and responsibly. Such standards should also provide guidance on how complex medical information should be presented in user-friendly, clear language to patients. Methods to coordinate release of data to patients with patient-clinician interactions are needed. Receiving critical data before the clinical team reviews it with their patient and had the opportunity to put the data into context can cause distress and misunderstandings for patients and clinicians. Finally, access outside of patient portals, which may be difficult to navigate or are not accessed for nearly half of Americans with cancer (78,79), is needed. Email and app-based information sharing should be prioritized to maximize the patient-centered benefits of information sharing.

Payment Reform for Digital Health Technologies

A central challenge to the dissemination of digital health technology in oncology is the lack of appropriate reimbursement for such tools (80). In particular, in the United States, a fee-for-service system may force oncology clinicians to choose between traditional, well-reimbursed care and innovation and patient-focused digital health tools that are not currently reimbursed. The slow but steady transition to value-based payment may incentivize use of relatively inexpensive and scalable digital health tools in cancer care that could eventually translate to improved clinician efficiency and better patient outcomes.

In the short-term, more focused reimbursement strategies are needed. The COVID-19 pandemic forced payers to provide much needed adequate reimbursement for telemedicine and other virtual care services; the specter of this reimbursement ending will pose large challenges for the oncology care system and for patients who wish to remain at home for routine oncology care. Recent randomized trials show that routine collection of PROs during cancer treatment leads to improved physical function, symptom control, and quality of life (81) while reducing acute care utilization (82). Cost savings of large-scale PRO collection are yet to be established, however, web-based PROs are cost-effective in conditions such as lung cancer (83). Medicare and private payers should consider full reimbursement of expenses related to electronic PRO implementation and maintenance to disseminate these benefits to broader systems. Such payers ought to consider incentives—potentially additional reimbursement or other preferred designations—for technologies that meet the aforementioned regulatory standards for equitable representation in testing and bias mitigation. Concordant with adequate reimbursement, PROs could be incorporated as a performance evaluation measure and included with best practices to ensure adequate quality of PRO tools.

Conclusion

The COVID-19 pandemic and associated stay-at-home orders forced clinicians, patients, and policy makers to envision new ways to deliver oncology care. Although this acceleration benefited many patients, it also exposed potential flaws in the digital health ecosystem. Without rapid solutions to these

critical issues or simplification of clinical workflows, digital health technologies will be of limited utility in oncology practice. Stemming from the proceedings of a 2020 workshop convened by the National Cancer Policy Forum of the National Academies of Sciences, Engineering, and Medicine, this article summarizes applications of digital health technologies in cancer care, the impact of the COVID-19 pandemic in accelerating uptake, and opportunities for clinicians, health systems, and policy makers to facilitate broader, patient-centric integration of digital health in cancer care. We highlight opportunities related to standardizing EHR data to enable interoperability, increasing patient access to and control of health data, and establishing payment reforms to offset costs of digital health infrastructure.

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REVIEW

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Data Availability

All de-identified data generated or analyzed during this study is available upon request. No new data were generated or analysed in support of this research.

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