Digital Transformation of Cancer Care in the Era of Big Data, Artificial Intelligence and Data-Driven Interventions: Navigating the Field

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Abstract

Objectives: To navigate the field of digital cancer care and define and discuss key aspects and applications of big data analytics, artificial intelligence (AI), and data-driven interventions.

Data Sources: Peer-reviewed scientific publications and expert opinion.

Conclusion: The digital transformation of cancer care, enabled by big data analytics, AI, and data-driven interventions, presents a significant opportunity to revolutionize the field. An increased understanding of the lifecycle and ethics of data-driven interventions will enhance development of innovative and applicable products to advance digital cancer care services.

Implications for Nursing Practice: As digital technologies become integrated into cancer care, nurse practitioners and scientists will be required to increase their knowledge and skills to effectively use these tools to the patient's benefit. An enhanced understanding of the core concepts of AI and big data, confident use of digital health platforms, and ability to interpret the outputs of data-driven interventions are key competencies. Nurses in oncology will play a crucial role in patient education around big data and AI, with a focus on addressing any arising questions, concerns, or misconceptions to foster trust in these technologies. Successful integration of data-driven innovations into oncology nursing practice will empower practitioners to deliver more personalized, effective, and evidenced-based care.

Keywords: artificial intelligence; big data; data-driven interventions; digital cancer care; digital transformation; data analytics

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Introduction

Gradual advances in digital technology over the last 20 years have resulted in an increase research on the digital transformation of healthcare[1–4] and implementation of digital health.[5,6] While one could argue that the digital transformation of healthcare is concerned more with the evolution of healthcare as an industry (e.g., evolution in processes, business model, domain applications, cultural and organizational changes), digital health is more concerned with the practical applications of digital technologies in clinical care and their use in everyday healthcare practices.[4,7]

The surge in these applications is only feasible because of changes across several domains. First, the exponential increase in the use of digital devices that create and/or capture data, as well as the expansion of data storage capacities and computational power, have allowed for the processing and analysis of large-scale, complicated databases at incredible speed.[1,3] These advances have facilitated the creation of more complex machine learning (ML) and artificial intelligence (AI) systems for use in various aspects of health care.[8] Second, the widespread adoption of electronic health records (EHRs) and digital health tools (e.g., next-generation sequencing (NGS), wearable devices, Internet of Things (IoT), mobile apps, social media) has led to the generation of massive amounts of structured and unstructured patient data.[9] Third, advances in the fields of multi-omics[10,11] and imaging[12–14] have provided deeper insights into the molecular basis of cancer that enabled a more precise understanding of the disease and paved the way for more targeted (precision) treatments.[15–18]

In oncology, digital technologies are used to improve cancer treatment outcomes through the use of predictive analytics, decision support systems, and precision health interventions.[16–19] The derived data-driven tools have the potential to optimize the use of resources; aid in clinical decision-making; and significantly improve patient outcomes.[20,21] The realization of the potential value of digital technologies has resulted in a growing body of evidence that supports the design, development, and evaluation of digital health interventions in oncology and cancer care.[22] The purpose of this article is to provide an overview of the field of digital cancer care, with particular attention to big data technologies, AI, and data-driven interventions.

Data-driven interventions

The term "data-driven" emphasizes the central role of data in informing and shaping the intervention(s). This approach contrasts with previous digital interventions that relied more on traditional, heuristic, or expert (i.e., human)-driven approaches. Historically, digital interventions in healthcare were limited in scope and relied on basic statistical methods and expert opinion to guide their design and implementation. While valuable, these approaches have faced challenges in scaling and adapting to the evolving healthcare landscape. With the advent of big data and sophisticated analytical approaches (e.g., AI and ML), data-driven interventions can harness the power of large-scale health data sets to deliver more targeted, personalized, and effective, prospectively autonomous healthcare solutions (see section ‘Levels of AI automation in Digital Cancer Care’).[23,24]

Data-driven interventions in healthcare offer several advantages over previous digital interventions.[25–27] First, they enable a more comprehensive understanding of complex and multimodal data (i.e., different types of data that spans a variety of contexts and/or modalities, like imaging, text, EHRs, genetics) by leveraging advanced algorithms and computational power. This approach allows for the identification of previously unrecognized data patterns and insights that may lead to more accurate and informed decision-making. Second, data-driven interventions can be more easily adapted and fine-tuned in response to changes in data or new clinical evidence. This attribute ensures that healthcare solutions remain relevant and effective over time. Finally, data-driven interventions facilitate a more personalized approach to healthcare by utilizing individual, continuous patient data (e.g., wearables, IoT) to tailor interventions to specific needs, preferences, and circumstances. This personalized approach will improve patient outcomes and overall healthcare efficiency.

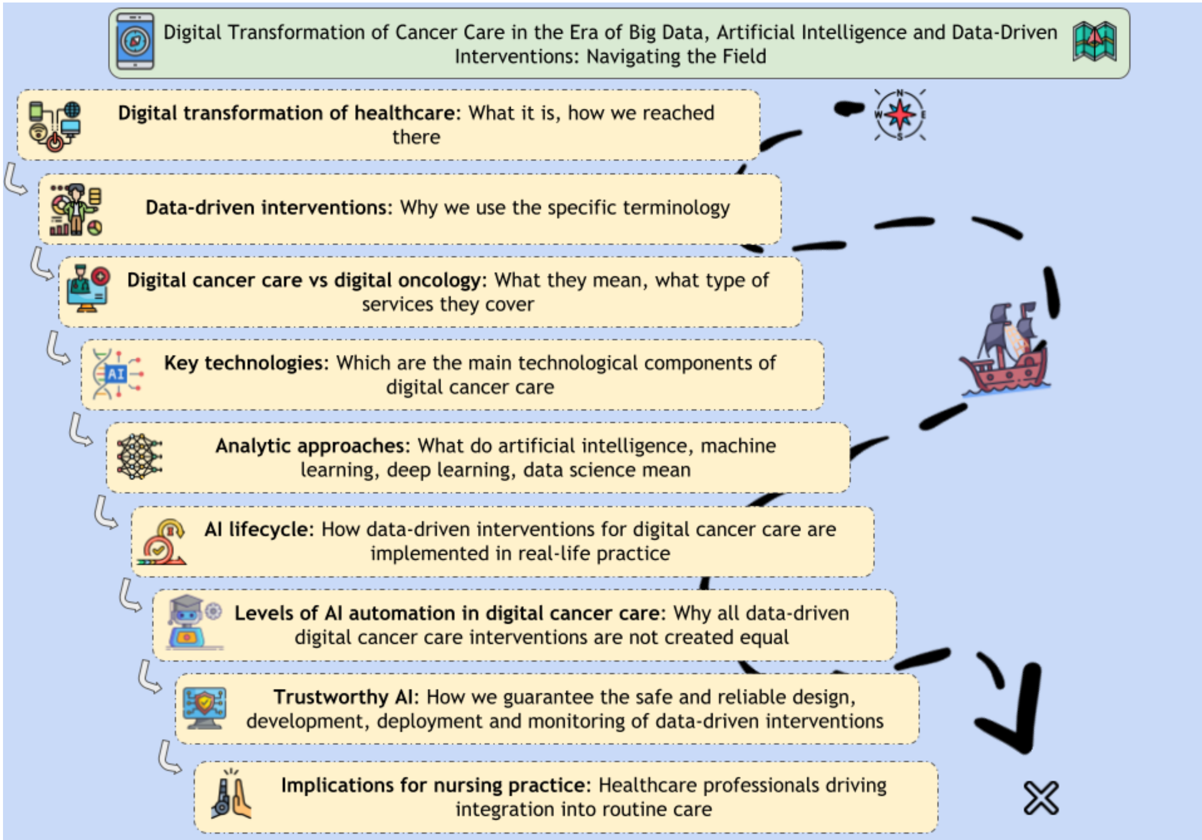

Figure 1: Structure of the article

Digital oncology and digital cancer care

Distinct and overlapping areas of service exist across the cancer care continuum (Table 1).[28] With the ongoing changes in cancer services,[28] it is important to distinguish between the terms: oncology and cancer care. Oncology is a branch of medicine that specifically deals with the prevention, diagnosis, and treatment of cancer.[30] Cancer care can be thought of as a broader term that encompasses the medical aspects of cancer management, as well as the use of an interdisciplinary approach to support patients throughout their cancer trajectory.[28] The provision of comprehensive cancer care involves the patient working together with a transdisciplinary team that includes physicians, nurses, dieticians, psychologists, pharmacists, physiotherapists, and social workers. In this context, while oncology is a vital component, cancer care goes beyond the diagnosis to integrate the diverse expertise of a variety of health care professionals to address complex health needs of patients living with cancer.

In a similar fashion, digital oncology focuses on the application of technological advances to the medically oriented fields of cancer prevention, diagnosis, and treatment. In contrast 'digital cancer care', that incorporates the cancer care spectrum,[28] involves the integration of digital and data-driven methods to enhance the overall standards of cancer care management and improve patient outcomes. While both digital cancer care and digital oncology use similar digital tools and technologies (e.g., EHRs, telehealth services, mobile apps, wearable devices, and ML algorithms), how these technologies are used and the specific interventions they support may differ. Digital cancer care interventions focus more on symptom management, patient engagement, adjustment to cancer, and wellness monitoring.[31] Digital oncology interventions are being developed to improve decision-making, personalize treatment options, and facilitate better communication and coordination among healthcare professionals, patients, and family caregivers.[32]

Table 1. Domains of care across the cancer continuum.[28]

Domain of cancer care	**Description**	**Services**
Prevention and Early Detection	This area focuses on reducing the risk of developing cancer and detecting it at an early stage when it is more treatable.	Services include screening programs, genetic testing, risk assessment, and promotion of a healthy lifestyle.
Diagnosis and Staging	This area involves the accurate identification and characterization of the cancer, including determining its type, location, and extent of disease (stage).	Services in this area include imaging studies (e.g., magnetic resonance imaging (MRI), computed tomography (CT), or positron emission tomography (PET) scans), biopsy procedures, and laboratory tests.
Treatment and Management	This area encompasses various therapeutic approaches to eliminate or control cancer growth. Services include surgery, radiation therapy, chemotherapy, immunotherapy, targeted therapy, and/or hormone therapy.	Supportive care, such as pain management, nutrition support, and psychological counselling are critical components of this layer.
Supportive Oncology,[29] Palliative Care and End-of-Life Care	This area focuses on effectively managing the long-term effects of cancer and its treatment across the continuum of cancer care and the provision of end-of-life care when necessary.	Services include monitoring for recurrence, assessment and management of symptoms and other adverse effects, rehabilitation, promotion of a healthy lifestyle, and the provision of palliative care to decrease symptoms and improve quality of life.

It should be noted that data-driven digital cancer care addresses the same users and health system needs that were mapped in the World Health Organization's 'Classification of Digital Health Interventions'.[33] In line with this classification, digital cancer care requires:

- Client-based interventions – the focus is on individuals seeking health services, including health promotion and education, self-assessment and diagnosis, and self-care support.
- Healthcare provider-based interventions – the focus is on health professionals with a view towards supporting clinical decision-making, inter-clinician communication, and patient/family-clinician communication.
- Health system manager-based interventions – the focus is on health system management, health care financing, and governance structures that support supply chain management, financial transactions, and workforce management.
- Data service-based interventions – the focus is on the generation, aggregation, analysis, and dissemination of health data that aids in public health monitoring, data exchange, and data analysis for decision-making.

Key Components of Digital Cancer Care and Data-Driven Interventions

Key technological components of digital cancer care are presented in Table 2. Integration of these components can create novel and complex, 'digital health' interventions.[84–86] These data-driven interventions leverage vast amounts of data generated from numerous sources to identify previously unknown patterns that can generate new knowledge, optimize resource allocation, monitor treatment responses, guide clinical decision-making, and personalize care.

Table 2. Key technological components of digital cancer care

Component	**Description**	**Comments**
EHRs[34]	EHRs are foundational to digital cancer care as they facilitate access to patient data; streamline communication among members of transdisciplinary healthcare teams; and enable informed decision-making.	Because EHRs contain comprehensive information on patients' medical histories, treatments, and test results, these data facilitate the ability of professionals from various disciplines to collaborate and develop personalized care plans across the continuum of cancer care.
Telehealth[35–37]	Telehealth approaches allow for remote consultations, monitoring, and support of cancer patients by a variety of healthcare professionals.	As evidenced during the COVID-19 pandemic,[38] this holistic approach to care can help to improve patients' overall well-being, treatment adherence, and satisfaction with care.
Mobile Health (mHealth)[36,39,40], IoT[41–44] and Wearable Technologies[36,45,46]	mHealth apps and wearable devices can track symptoms, detect a variety of health events, and monitor adherence with various lifestyle management strategies. IoT devices (i.e., sensors) and wearables can track patients' vital signs, medication adherence, and lifestyle behaviors and provide valuable data to tailor and personalize patients' management plans.	IoT can enhance communication between healthcare professionals and patients, enable the provision of care remotely, and facilitate timely interventions with the ultimate effect of improving patient outcomes.
Cloud services[47–49]	Cloud services play a crucial role in the digital transformation of cancer care because they provide scalable, secure, and accessible platforms to manage and analyze large volumes of healthcare data.	Cloud-based infrastructures allow healthcare organizations to efficiently store, share, and process complex cancer-related data; facilitate collaboration among multidisciplinary teams; and speed the development of data-driven interventions. In addition, cloud services enable the deployment of ML models and advanced analytics tools that can support real-time decision-making in cancer care.
(electronic) Patient-Reported Outcome Measures (PROMs / ePROMs)[34,50–56]	PROMs and ePROMs capture patients' perceptions of symptoms and quality of life.	The integration of PROMs into digital cancer care allows healthcare professionals from different disciplines to tailor care plans, monitor patients' well-being, and evaluate the effectiveness of interventions across the continuum of cancer care.
Big Data[57–59] and AI[60,61]	The increased availability of large amounts of data in cancer care has led to the development of big data AI technologies for early detection,	Recent applications of AI and Large Language Models (LLMs) such as ChatGPT,[62] that shows "sparks of artificial general intelligence",[63]

Component	Description	Comments
	diagnosis, treatment planning, and prediction of treatment outcomes.	may improve cancer care through the analysis of large volumes of textual information. This approach will allow for the identification of patterns, trends, and associations that were not easily discernible through traditional methods. For instance, LLMs can facilitate automatic extraction of critical clinical information from medical records,[64,65] such as cancer type, stage, treatment history, and response to therapy.
Chatbots[66,67]	Chatbots can serve as virtual assistants. They can provide patients with 24/7 access to accurate information about their condition, treatment options, and side effects, as well as answer frequently asked questions. Chatbots can help monitor patient-reported symptoms, offer personalized advice for symptom management, and facilitate communication between patients and their healthcare team.	Through automation of a variety of tasks, chatbots can help reduce the workload of healthcare professionals and improve the overall cancer care experience for patients, making it more efficient, patient-centered, and accessible.
Imaging[68,69]	Advanced imaging techniques (e.g., MRI, CT, PET, ultrasound), provide non-invasive methods to visualize tumors and assess their characteristics.	The integration of AI and ML into imaging analyses can enhance the precision and efficiency of cancer care through the automation of image interpretation, reduction in the variability in interpretations, and the identification of subtle patterns that may be missed by the human eye.[68]
Genomics[70–73]	Genomics concentrates on the study of cancer cells' genomic composition to obtain a better understanding of the fundamental processes associated with the development and spread of cancer. These types of analyses can be used to guide diagnostic, prognostic, and therapeutic choices.	The integration of genomic data with AI into clinical practice offers tremendous potential for enhanced accuracy, effectiveness, and overall outcomes, because treatments will be tailored to the genomic signature of an individual patient's cancer.
Multi-omics[59,74]	Multi-omics approaches, that integrate genomic, transcriptomic, proteomic, and metabolomic data, hold great promise for advancing our understanding of cancer biology and improving patient care. By generating a comprehensive molecular profile of a patient's tumor, multi-omics can provide insights into the underlying mechanisms driving cancer progression and treatment response.	This information can be leveraged to develop personalized treatment strategies and identify novel therapeutic targets, that lead to more effective and precise cancer care.
Blockchain[75,76]	Blockchain technology has the potential to revolutionize cancer care by providing secure, transparent, and decentralized solutions for data management and sharing. It can provide additional layers of privacy and safety to be able to use new approaches of de-centralized ML,	In cancer care, blockchain can be used to enhance patient privacy, streamline medical record management, and ensure the integrity of clinical trial data. Furthermore, it can facilitate secure data sharing between healthcare providers, researchers, and patients, foster

Component	Description	Comments
	federated learning,[77–80] where all sites are able to keep their data and train ML models locally, while they create a cumulative, collective AI model.	collaboration, and enable the development of more effective treatments.
Augmented Reality (AR)[76,81]	AR overlays digital technology onto one's real-life environment and objects via use of graphics, sound, or other sensory enhancements.	For healthcare professionals, AR can be utilized for medical training, surgical planning, and real-time guidance during procedures; enhance clinician's accuracy, and reduce complications. For patients, AR can be used to educate patients about their cancer diagnosis and its treatments in a more easily understood and engaging manner. The use of AR can empower patients to make more informed decisions about their care.
Digital twins[82,83]	Digital twins, virtual replicas of physical systems or processes, offer a powerful tool to simulate and predict the behavior of cancer cells and treatment responses. By creating digital twins of tumors, researchers can model the complex interactions between cancer cells, the tumor microenvironment, and therapeutic agents.	This approach can help to identify potential treatment strategies, optimize drug dosing, and minimize side effects. In clinical settings, digital twins can facilitate personalized treatment planning and enable clinicians to make data-driven decisions, ultimately improving patient outcomes.

Analytic Approaches in Digital Cancer Care

Digital cancer care involves various analytic approaches (Figure 2). Several terms (explained below) are often used interchangeably to indicate the same approach.

AI[87] focuses on the development of computational systems and algorithms capable of performing tasks that typically require human general intelligence. These tasks encompass a wide range of cognitive functions, including learning, reasoning, problem-solving, perception, natural language understanding, and decision-making. AI aims to mimic, augment, or surpass human intelligence by creating machines that can adapt to new situations, recognize patterns, and draw inferences from data to make informed decisions autonomously or in collaboration with humans.

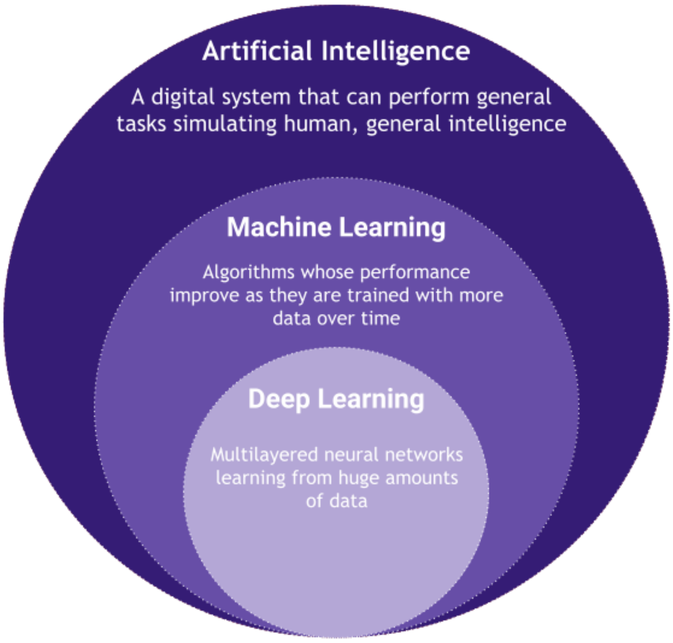

Figure 2: Non exhaustive representation of the intersection between AI, ML, DL

ML[87] is a subset of AI. It encompasses algorithms that computers use to learn from data without explicit programming. These algorithms become more accurate and effective as they are exposed to more data, allowing them to 'learn' from experience and "adapt" to new information. Related to ML, Automated ML (auto-ML)[88] is an analytical approach that has recently gained traction and revolutionized the modelling domain. Auto-ML refers to the automated selection, optimization, and evaluation of ML algorithms for a given dataset. Auto-ML has the potential to accelerate the modeling process and decrease the barriers to entry for non-experts in the field of ML. This approach has the potential to benefit digital cancer care by increasing the efficiency and accessibility of data-driven interventions.

Deep learning (DL)[87] is a specialized form of ML algorithms. It focuses on the use of deep neural networks with multiple hidden layers to model complex patterns and representations in large, high-dimensional datasets. These networks are designed to mimic the human brain's structure and function, enabling DL algorithms to handle more intricate and abstract data representations. DL techniques have been especially successful in tasks such as image and speech recognition, natural language processing, and reinforcement learning, where traditional machine learning approaches may struggle.

Data science[89,90] is a broader field that encompasses the collection, analysis, and interpretation of data using various techniques, including AI, ML, and other statistical methods. While AI, ML, and deep learning are primarily focused on the development of intelligent algorithms, data science is concerned with the broader processes involved in the management, analysis, and interpretation of data to inform decision-making.

The landscape of AI and ML covers a wide range of techniques and methods that can be applied to various tasks and problems in healthcare.[91–93] Table 3 provides an overview of AI and ML techniques that are relevant healthcare, along with examples of practical applications.

Table 3. Overview of analytic techniques in AI and ML with examples of practical applications in healthcare.

Analytic technique	Description	Practical application in healthcare
Supervised learning[94,95]	A type of ML where an algorithm learns from available labeled training data to make predictions or classifications. In this approach, a model is trained using input-output pairs, where the output is the desired outcome (label). Supervised learning techniques include classification (categorizing data into predefined classes or categories) and regression (predicting a continuous value).	In healthcare, supervised learning can be used to diagnose the stage of cancer based on medical images or predict patient readmission rates based on electronic health records.
Unsupervised learning[94,95]	A type of ML where an algorithm identifies patterns in data without any labeled output. The goal is to find underlying structures or relationships in the data. Common techniques include clustering (grouping similar data points) and dimensionality reduction (reducing the number of variables while preserving essential information).	In healthcare, unsupervised learning can be used to identify patient subgroups with similar medical conditions or to reduce the complexity of large-scale genomic data for analysis.
Reinforcement learning[94,95]	A type of ML where an algorithm learns to make decisions by interacting with an environment and receiving feedback in the form of rewards or penalties. The goal is to find an optimal policy or sequence of actions that maximizes cumulative rewards over time.	Applications in healthcare can include optimizing treatment plans for patients with chronic conditions, training robots for surgical assistance, or coordinating multiple agents in emergency response scenarios.
Natural language processing (NLP)[96,97]	A subfield of AI focused on enabling computers to understand, interpret, and generate human language. Techniques in NLP include sentiment analysis (identifying emotions in text), text classification (categorizing documents), and information extraction (identifying entities and relationships in text).	In healthcare, NLP can be used to analyze patient feedback, categorize medical literature.
Computer vision[98,99]	A field of AI that focuses on enabling computers to interpret and understand visual information from the world. Techniques in computer vision include image recognition (identifying objects in images), object detection (locating specific objects in images), and image segmentation (dividing an image into distinct regions).	In healthcare, computer vision can be used to analyze medical images for disease detection, such as identifying tumors in MRI scans or detecting diabetic retinopathy in eye images.
Speech recognition[100,101]	The process of converting spoken language into written text, while speech synthesis[101] is the process of generating human-like speech from written text.	Applications of speech recognition and synthesis in healthcare can include voice assistants for patient care, transcribing doctor-patient conversations, and facilitating communication for people with speech impairments.
Recommender systems[102,103]	Algorithms that provide personalized recommendations or suggestions to	In healthcare, recommender systems can be used to suggest personalized

Analytic technique	Description	Practical application in healthcare
	users based on their preferences, behaviors, or interactions.	treatment plans, recommend relevant medical literature to clinicians, or suggest lifestyle changes for patients based on their health data.
Anomaly detection[104,105]	A technique used to identify unusual patterns or outliers in data that deviate from the norm.	Applications in healthcare can include detecting fraudulent claims in insurance, identifying potential data breaches in electronic health records, and monitoring patient vital signs for early warning signs of deterioration.
Time-series analysis[106]	A collection of methods used to analyze and model time-ordered data. Techniques include forecasting (predicting future values based on historical data) and pattern recognition (identifying trends, cycles, or other structures in the data).	In healthcare, time-series analysis can be used to forecast patient admissions, analyze disease progression over time, or monitor the effectiveness of treatment interventions.
Network analysis[107,108]	A set of techniques used to study the relationships and interactions between entities represented as nodes in a graph or network.	In healthcare, network analysis can be applied to study social networks of patients or healthcare providers, understand the spread of infectious diseases, or analyze the interactions between different genes or proteins in biological systems.

Besides advances in analytic approaches, several challenges should also be mentioned. One challenge is data curation,[88] , that involves the cleaning, labeling, and organization of large amounts of complex and heterogeneous data from various sources (e.g, EHRs, genomics, imaging). Proper data curation is critical to ensuring the quality and reliability of ML models, because if models are trained on poorly curated data the results may be misleading or suboptimal.

Another challenge is the various types of data drift that can occur, such as concept drift[109,110] and covariate shift.[109] Data drift refers to changes in the underlying patterns or relationships between variables over time and if it not accounted for in the analysis the model's performance can degrade. To address data drift requires continuous monitoring of model performance and regular updates to ensure that the model remains accurate and relevant to the current state of the data.

Monitoring ML models in digital cancer care is a complex task because it involves tracking the performance of models over time and detecting potential issues that may arise.[111] This approach includes monitoring model accuracy; ensuring that the model is robust and interpretable, and that the acquisition and modelling of data involves evaluation of the ethical principles (e.g., fairness, privacy).

Lastly, the integration of ML within existing services and processes associated with digital cancer care will be a significant challenge.[22,112,113] It is essential to ensure that these models can be seamlessly integrated into clinical workflows, decision support systems, and other healthcare services to maximize their utility and impact. To achieve this goal requires collaborations among data scientists, data/ML engineers, healthcare professionals, patients, family caregivers, and other stakeholders to design and implement effective solutions that address the unique needs and constraints of cancer care.

Lifecycle of Data-Driven AI Systems in Digital Cancer Care

A comprehensive AI lifecycle involves many different stages, typically comprising data gathering, data pre-processing, feature engineering (i.e., creating variables from unhidden patterns in data), model selection, training, validation, deployment, and monitoring (Figure 3).[114–116] Each of these stages is crucial to the success of a data-driven intervention in cancer care, as they ensure that the developed models are up-to-date, accurate and effective in addressing the specific problem at hand. Moreover, these stages promote a more iterative and adaptive approach to the data-driven system development, allowing for continuous improvement and adjustment based on new data, clinical evidence, or changing healthcare needs.

While much of the current digital health literature focuses on the modeling performance of various analytical techniques, it is important to recognize that modeling is just a small part of the complete lifecycle of an AI system (Figure 3).[114–116] In real-world settings, the debate over which model performs best can be less relevant, as factors such as data quality, scalability, interpretability, and integration with existing workflows play a more significant role in determining the overall effectiveness and applicability of a data-driven intervention. Moreover, the adaptability and maintainability of a system in a dynamic healthcare environment can significantly impact its long-term success.

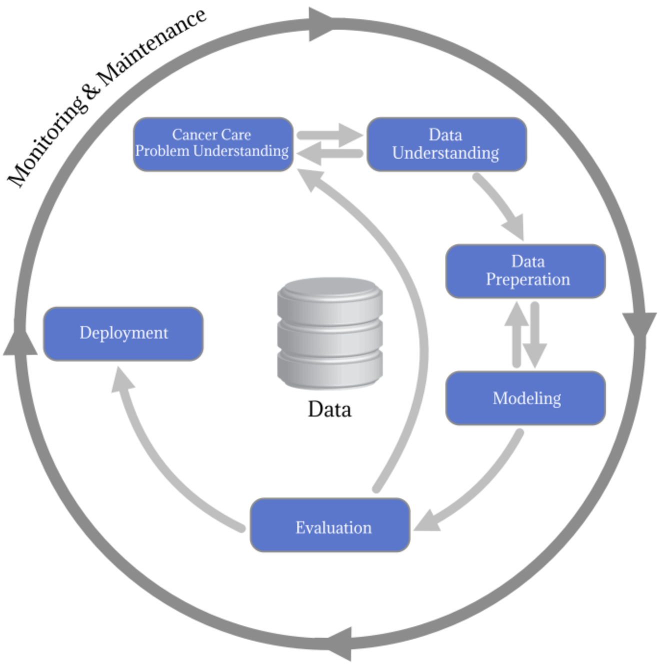

Figure 3: AI lifecycle (based on the CRISP-DM model[116])

It is essential to expand the discussions around digital cancer care and include additional topics when evaluating the performance and applicability of AI systems. Building a reliable AI system is a complex problem, involving not only the development of a high-performing model but also the integration of software engineering, data engineering, and DevOps (i.e., a set of practices that combines software development and Information Technology (IT) operations, aiming to shorten the development lifecycle and provide continuous delivery of high-quality software by fostering collaboration, automation, and integration across teams) principles. These factors, combined with ethical considerations, data privacy regulations, and the need for effective collaboration between stakeholders, can contribute synergistically to the multidimensional nature of the challenge.

Software, data and machine learning engineering as well as data science practises play a vital role in ensuring the seamless integration and execution of the AI lifecycle stages.[7,111,114,117] Software engineering provides the foundation for building scalable, maintainable, and reliable software (i.e., AI system), facilitating collaboration between different stakeholders and promoting best practices in code development and system architecture. Data engineering focuses on efficient data storage, processing, and management, enabling the effective use of healthcare data in the development and deployment of ML models. Machine learning engineering bridges the gap between data science and software engineering, applying ML algorithms to real-world problems and ensuring their successful integration into the larger AI system. Lastly, data science principles guide the analysis and interpretation of complex healthcare data, enabling the extraction of meaningful insights and informing the development of accurate and impactful ML models.

The design, development, and deployment of data-driven digital interventions require a multidisciplinary approach to effectively integrate technological and clinical expertise around patients' needs.[118,119] Technological experts are responsible for the development and implementation of the software, hardware, and networking infrastructure necessary to support data-driven cancer care interventions. Clinical experts have in-depth knowledge of cancer care, including diagnosis, treatment, and survivorship. They can provide insights into the practical challenges associated with the implementation of data-driven interventions in "real world" clinical settings and can help ensure that the interventions are aligned with best practices in cancer care.

Integration of technological and clinical expertise requires effective communication. Today, this is facilitated by modern project management paradigms, such as Agile.[118,119] Agile methods, that are popular in software engineering, are being evaluated in healthcare,[118,120,121] including cancer care.[122,123] Agile methods emphasize flexibility, rapid prototyping, and continuous feedback, making them attractive options for complex and evolving digital cancer care projects.

However, the application of project management methods (e.g. Agile) that were developed for specific purposes (i.e. software engineering) to different problems and audiences (i.e., data science problems, stakeholders from diverse expertise and practice backgrounds) comes with its own costs.[124–126] Data science projects frequently require extensive exploration and experimentation.[127] In many cases, the outcome or feasibility of a product may not be known until after several iterations of the experiment. This inherent uncertainty makes it challenging to adhere to strict timelines and plans for specific deliverables. In addition, the success of data science and ML projects depends to a large part on the quality and availability of data.[125,127] Data acquisition and pre-processing can consume a significant amount of time and resources, making it hard to maintain the pace of an Agile process. Unforeseen issues with data quality or accessibility can cause serious delays and derail Agile project schedules.

It is crucial for digital transformation teams in cancer care to recognize and address these challenges, and explore different methods of project management for complex, data-driven interventions.[124] This approach will enable expert groups to collaborate more effectively to develop and deploy truly applicable data-driven digital cancer care products.

Levels of AI Automation in Digital Cancer Care

We must acknowledge that not all data-driven interventions in digital cancer care are created equally in terms of their level of AI automation.[23,24] The degree to which AI systems can autonomously perform tasks, make decisions, and generate insights varies significantly. This variability has substantial implications for their adoption, utility, and impact on patient care. Health care professionals, researchers and stakeholders need to understand the varying levels of AI automation in order to be able to evaluate the potential benefits and limitations of AI systems in cancer care, and to ensure that the appropriate safeguards and oversight mechanisms are in place to optimize patient outcomes and uphold the highest standards of care.

AI systems can be categorized into different, broad levels of automation, ranging from systems that merely assist human decision-making to those that are entirely autonomous (Figure 4).[23,24] At the lower end of the automation spectrum, AI systems may serve as decision support tools that provide healthcare professionals with additional information or recommendations to enhance clinical judgment. These systems rely heavily on human expertise and intervention to drive the decision-making process that ensures that AI-generated insights are contextualized and validated by human expertise.

As the levels of AI automation increase,[23,24] systems may assume a more active role in the decision-making process, with the capacity to autonomously analyze data, identify patterns, and generate recommendations without direct human input. While these systems will require human oversight and validation, they will reduce the cognitive load on healthcare professionals and streamline the decision-making process.

At the highest level of automation, AI systems may be capable of making fully autonomous decisions (e.g. personalized treatment planning, prognostic predictions).[23,24] These systems may be able to operate with minimal or no human intervention by leveraging advanced algorithms and large-scale data analyses to generate insights and recommendations. However, achieving this level of automation presents numerous challenges, including ensuring the safety, accuracy, and ethical considerations of AI-generated decisions.

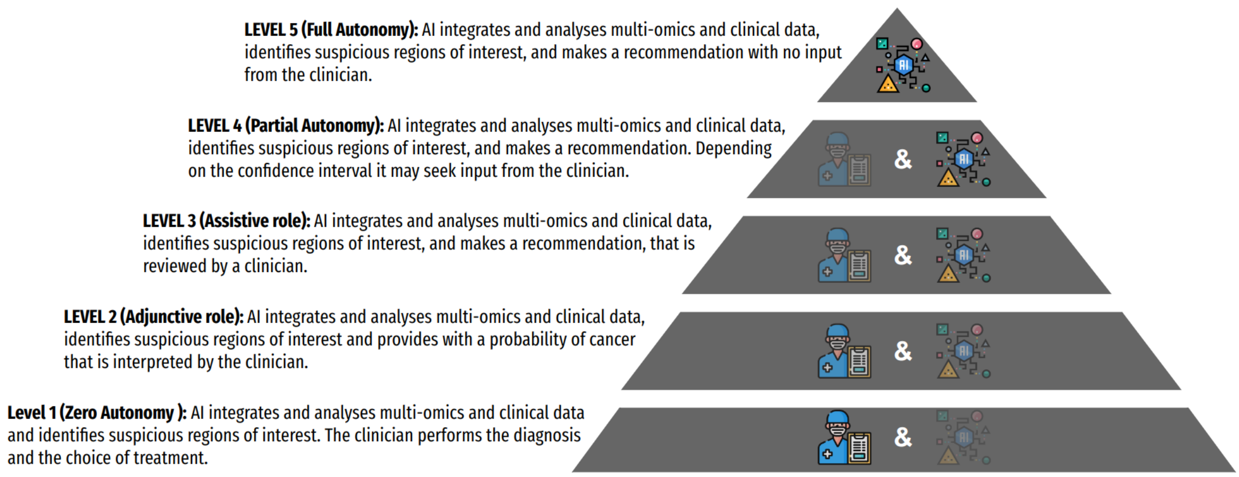

Figure 4: Levels of AI automation in digital cancer care

Trustworthy AI

To ensure the safety, accuracy and ethical application of data-driven interventions, Trustworthy AI[128–130] is of paramount importance in digital cancer care to foster trust among healthcare professionals, patients, family caregivers, and other stakeholders. Trustworthy AI encompasses several key principles that need to be considered and adhered to throughout the AI lifecycle (Table 4).

Table 4. Key principles of Trustworthy AI

Principle	Description	Comments
Transparency and Explainability[128–130]	AI systems should be designed to provide clear, understandable explanations for their decisions and predictions.	In the context of cancer care, providing insights into the reasoning behind AI-based recommendations can help healthcare professionals make more informed decisions and ensure that patients understand their care options.
Robustness and Reliability[128–130]	AI systems should be robust against various uncertainties, including noise in the data, incomplete information, and changing conditions.	Ensuring the reliability of AI systems is crucial for maintaining the quality of care and preventing potential harm to patients. Regularly updating and validating AI models using real-world data can help improve their robustness and reliability.
Fairness and Bias[128–130]	AI systems should be designed to ensure fairness and avoid potential biases that may lead to discriminatory outcomes.	In cancer care, this involves considering factors such as age, gender, ethnicity, and socioeconomic status when developing and evaluating AI models.
Privacy and Data Security[128–130]	AI systems should be designed to ensure that data privacy and security are maintained at all times.	The protection of sensitive patient data is of paramount importance in healthcare.
Accountability and Responsibility[128–130]	Stakeholders, including technical experts, healthcare professionals, and institutions, should be held accountable for the decisions and actions of AI systems. Ethical guidelines and regulatory frameworks should be in place to ensure that AI systems are used responsibly and that any unintended consequences are addressed promptly.	Establishing clear lines of accountability and responsibility is essential for the successful deployment of AI systems in cancer care.
Human-centric AI[128–130]	AI systems should be designed to augment and support human decision-making rather than replace it.	In cancer care, AI should be used as a tool that empowers healthcare professionals and patients, providing them with valuable insights and recommendations while allowing them to maintain control over the decision-making process.

Conclusions

To harness the potential of big data,[57] AI, and data-driven interventions in cancer care, it is crucial to navigate the associated advantages, complexities, challenges, and opportunities. An increased understanding of the unique features of data science, data analytics, and automation is essential for successfully designing and developing data-driven interventions in cancer care. Compliance with Trustworthy AI principles and frameworks is critical to the ethical and safe application of AI in cancer care.

The digital transformation of cancer care has significant implications for oncology nursing practice. As digital technologies become integrated into cancer care, nurse practitioners and scientists will be required to increase their knowledge and skills to effectively use these tools to the patient’s benefit. An enhanced understanding of the core concepts of AI and big data, confident use of digital health platforms, and ability to interpret the outputs of data-driven interventions are key competencies.

Nurses in oncology will play a crucial role in patient education around big data and AI, with a focus on addressing any arising questions, concerns, or misconceptions to foster trust in these technologies. Successful integration of data-driven innovations into oncology nursing practice will empower practitioners to deliver more personalized, effective, and evidenced-based care.

Conflicts of Interest

The authors have no conflict of interest to declare.

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Highlights:

- As digital technologies become integrated into cancer care, nurses will need to increase their knowledge and skills to effectively use these tools to improve patient care.
- Nurses will need to understand the core concepts of AI and big data; effectively use digital health platforms; and be able to interpret the outputs of data-driven interventions.
- Nurses will play a crucial role in patient education around big data and AI, ensuring that patients understand and trust relevant technologies and clarify any concerns and misconceptions.