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Oncology Informatics: Status Quo and Outlook

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Abstract
Oncology has undergone rapid progress, with emerging developments in areas including cancer stem cells, molecularly targeted therapies, genomic analyses, and individually tailored immunotherapy. These advances have expanded the tools available in the fight against cancer. Some of these have seen broad media coverage resulting in justified public attention. However, these achievements have only been possible due to rapid developments in the expanding field of biomedical informatics and information technology (IT). Artificial intelligence, radiomics, electronic health records, and electronic patient-reported outcome measures (ePROMS) are only a few of the developments enabling further progress in oncology. The promising impact of IT in oncology will only become reality through a multidisciplinary approach to the complex challenges ahead.

Oncology has undergone rapid progress, with emerging developments in areas including cancer stem cells, molecularly targeted therapies, genomic analyses for diagnostic and therapeutic stratification, and, most recently, individually tailored immunotherapy. These advances have expanded the tools available in the fight against cancer. Some of these have seen broad media coverage, often in line with the *hype cycle* model [1], and resulting in justified public attention. However, these achievements have only been possible due to rapid developments in the expanding fields of biomedical informatics and information technology (IT), a fact that often escapes public recognition. Exemplary advances in informatics methodologies and tools have been made in surgical and radiation oncology, in image processing for radiologic diagnostics and treatment, in histopathological classification as well as data analysis for follow-up assessment. These developments have not only resulted in increased efficiency of oncological procedures, but also in favourable survival rates, reduced treatment toxicity, and improved quality of life for many cancer patients [2, 3].

In modern clinical practice, tight integration of IT into workflows enables the efficient processing of rapidly ac-

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cumulating information enabling entirely new applications [4, 5]. There is an increasing interest in data mining of clinical narratives from electronic medical records to utilise diagnoses and clinical characteristics for the data-driven identification of clinical trial eligibility and especially for the prediction of clinical outcomes [6]. Although the shift from paper to digital goes beyond availability and acquisition speed, the real improvement lies in the implementation of "unstructured-to-structured" data transformation. For data that is to be used in subsequent analyses, efficient mapping to computationally useable formats is essential [7]. While structured reporting alone may suffer from loss of "verbatim" information, it allows for an automated interpretation of meaning, enabling automated analyses otherwise not possible [8]. However, the transformation of unstructured data using natural language processing and other "intelligent" text parsing technologies can preserve the original textual context in addition to providing the structured data for analyses.

IT can help determine patterns emerging from traditional and high-throughput molecular data, improve diagnostics of new cancers, and assist stratification of existing cases. Emerging artificial intelligence methodologies, such as "deep learning", have been applied successfully, for example, to the detection of lung cancers on screening CT scans, breast cancers on mammography and skin cancers on digital photographs [9–12]. Furthermore, radiomic analyses of images have found new features that can be predictive of outcomes and may help determine care decisions [13]. While not every result is universally applicable [14], the use of machine learning technologies is on its way into decision support systems for imaging and other types of complex clinical data [14].

A better understanding of how we deal with information and make decisions can improve our decision-making process. By expanding our understanding of the clinical situation beyond laboratory and imaging values, a variety of parameters may become apparent [15], and, based on an IT-supported approach, criteria rarely implemented in decision-making can be identified [16]. Parameters not traditionally considered in stratification procedures are patient preferences and psychophysiological factors, which in the future may become better integrated into our data models [17]. So far, a major obstacle has been the lack of standardized collection procedures and notations for psychophysiological raw data to draw objective conclusions about these factors and their impact. Traditionally, data acquisition occurred in offices, outpatient clinics or trial units following a formalised schedule. With the spread of mobile technology, structured high-quality data (electronic patient-reported outcomes) can be submitted from the patients themselves and become directly integrated into their records [18]. It has been demonstrated that this is feasible in a general population [19–21], and the acceptance rates of such solutions both on the patient side and the side of healthcare providers appear high. Electronic patient-reported outcome measures (ePROMS) enable structured first-hand data and open up the possibility to analyse the psychophysiological background of a reported incident as patient-centred IT may soon be able to connect such reports with measurements from miniature, wearable sensors and devices [22]. Newer classes of machine learning applications will focus on integrating human perception and self-expressed observations with diagnostic tests and high-frequency measurements of physiological parameters to predict adverse events and allow early therapeutic interventions.

The amount of data from electronic health records, diagnostic procedures and molecular screening analyses provides new opportunities for diagnostics, therapy and event prediction. The proliferation of electronically accessible, patient-related data will also require new or modified regulations and will provide additional entry points for security threats. From this, a need will arise to re-evaluate aspects of confidentiality, consent and patient privacy. Besides the implementation of "best practice" data storage and handling procedure, new computational approaches, such as blockchain technologies, may potentially provide building blocks of future secure data transactions [5].

The increasing qualities and quantities of data available for patient-centric analyses in oncology lend themselves to new types of "artificial intelligence" approaches, such as machine/deep learning algorithms that enable insights into information that may not be intuitively accessible [23]. However, one of the difficulties of the complexity resulting from these algorithms, particularly in deep learning scenarios, is that we are not able to intuitively evaluate their results. Here, visual approaches have been designed to help us understand the essence behind that flood of data [24, 25]. There is a strong drive in the machine learning community to devise what is referred to as "interpretable or explainable methods" [26]. Even further, a sensible processing of the plethora of structured data may enable aided decision-making regarding complex oncological therapies by incorporating information such as patient preference and experience of the physician. In this respect, oncology informatics may eventually provide a personalised and individualised path for each patient through the often complex and multidisciplinary treatment algorithms.

The promising impact of IT in oncology will only become reality through a multidisciplinary approach to the complex challenges ahead.

Disclosure Statement

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Author Contributions

All authors contributed to the structure and writing of this review.

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