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Review Article

Breast Cancer Management and Coordination Using Artificial Intelligence

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Abstract

Breast cancer care is complex and requires a continuous interaction between patients, primary care providers and specialists. Communication among these providers is crucial for timely treatment, monitoring treatment compliance and adverse outcomes, as well as management of comorbidities. The director role of care management is; however, often unclear, and patient care gets fragmented along the course of treatment and worse in follow-up. Multidisciplinary team meetings play a central role in care planning and structured data collection. Nurse navigators can also play a crucial role in care allocation and guidance, becoming the pivotal determinant of breast cancer care. Here, automatic artificial intelligence (AI) driven planning and symptom tracking can facilitate their tasks, however, human intervention continues to remain vital to account for unexpected emergencies and psychosocial support. Unfortunately, collection of patient data and allocation of patients are often done by hand and across disorganized data sets, as system solutions are limited in crossing care providers. Collection of disease-specific outcome data and adverse effects is essential for predictive tool development. Sharing data among specialist and primary care providers enforces accurate allocation and tailoring, moreover, can solve challenges related to scarce resources, distance and costs. AI-enhanced tools can only be developed and support a well-coordinated, patient-centred cancer care system. In the real world, effective communication and data collection across care-providers is challenging in the current healthcare system.

Herein, we address the role of information technology and AI and discuss potential barriers in cancer care.

Keywords: *Artificial Intelligence; Breast Cancer; Predictive Tools; Care Coordination; Symptom Management*

Introduction

Cancer care is a complex process, often involving different specialists, diagnostic modalities and therapies for each patient. Appointments need to be scheduled across different departments and clinics, while central coordination is often missing. Patients are emotionally and physically affected by waiting times and communication errors between providers. In search for continuity of care and access to information, many patients opt for a second opinion, involuntarily making their care pathway increasingly complex [1,2].

With new digital solutions, addressing planning and communication in other industries (travel bookings, banking etc), patients have become more inclined for tele-solutions in their cancer care path which has created a traction for investment in the digital health market [3,4].

Cancer care, however, is currently lagging due to its information complexity. Providers resort to the multidisciplinary approach for the treatment of cancer patients due to involvement of specialists from different verticals for each patient [2,5-8]. In this paper, we map the current situation of breast cancer management, relate them to possible future models using artificial intelligence (AI) and emphasize on the research efforts to catch up with digital trends to support patient care management.

Care coordination

To improve individual care coordination and symptom management, we need to dissect the various stages of breast cancer care continuity. To capture this in a working model we simplify the 3 facets of care coordination as follows [2,5]: clinical medicine (what is needed, evidence-based, for each patient), approach to care (spectrum of patients' needs) and system solutions (human and machine support for delivery goals).

Clinical medicine

Integrated breast cancer care requires a multidisciplinary approach with a combination of primary care providers, radiologists, pathologists, nuclear medicine specialists, surgeons, medical and radiation oncologists. Often genetic, palliative and social counselling are necessary, ideally all of which are integrated into one multidisciplinary team. Tumour board (TB) discussion brings the two facets of clinical medicine and patient care approach together by inter-professional discussion of medical needs, evidence-based solutions, as well as specific patient needs in terms of performance, comorbidity, psycho-social and financial restrictions. However, because of volume often only complex cases are addressed. Today, there are several system solutions to support the TB constituting the third pillar [9-13] aiding in providing decision support [14-17]. National guidelines are the strong back bone of the current tools and clinical practice today. However, most of the references are based out of homogenous cohorts, not always translatable to all patients (accounting for national, cultural, even genetic differences). Integration of AI [17] using local data can transform these tools to allow decision support based on breast cancer subtype by utilizing genetic profiles combined with patient history. Similar learning loops with local data can improve advice quality of support including geographical difference in resources, as well as cultural and genetic variations.

Approach to care

Allocation of treatment and consultations are not determined solely by medical needs, drivers as individual patient's capacity to understand, travel, consent and financial resource parameters can be decisive. This complex decision-making process with multiple variables necessitates effective communication and coordination where TB briefing to primary care providers and nurse navigator can play an essential role. Integrating social and financial support can improve compliance, thus indirectly improving outcomes [9,18].

Automation tools that work based on a two way traffic mode can enable the system to take patients' needs into account and allow medical information to be shared with nurses and other care providers [9,13,16].

System solutions

Information technology (IT) can facilitate data collection and communication. Combined with AI, complex data from historical cohorts can be used to anticipate medical needs, risks as well as patients' decisions and response facts. Commensurate care coordination takes all the above factors into account, while allocating and guiding patients through their most suitable care path based on current guidelines. Ideally, the model focuses on maximizing the combinatorial power of IT processing and the socio-psychological judgement of human director intervention, allowing to steer coordination [19].

Clinical decision support systems and AI

Clinical decision support systems (CDSS) are finding their place in healthcare centres assisting healthcare professionals to make evidence-based decisions. Although, the current systems are based out of a population cohort that is essentially an oversimplification to delve into the details required for personalized breast cancer care. It is necessary to create smaller cohorts based on critical parameters that are essential to classify patients [20,21]. This will help create CDSS that are operational towards personalized medicine. Additionally, specialized CDSS containing decision support algorithms for individualized patient scenarios can be embedded into existing IT system based solutions already in use [22].

Diagnostic decision making

Workflow management system ideally requires the presence of rigorous workflow mapping. Keeping up with current trends in management guidelines and changing practice recommendations has caused clinical decision support systems and workflow optimization to suffer from lack of stratified cohorts. This delay in incorporation of validated guidelines causes incompetent workflow systems. These changing guidelines also hamper data collection because newer treatment methodologies may have different data points that are pertinent to the system. Mining clinical trial data sets and allowing prompt integration within the clinical decision support system could be of value in breast cancer care. As an example, Bacur., *et al*. suggest a clinical decision support system which can be easily modified to incorporate recent literature into the generic workflow module [23].

Role of nurse navigator in breast cancer care continues to remain vital in providing curated medical information, emotional support. A central person in this process is essential, a suitable approach would be a nurse navigator, due to their maximum contact time with patients while they are undergoing treatment [24]. In a study conducted in Canada in 2015, patients reported better understanding of information and felt satisfied with the information provided to them by the nurse navigator [25].

Professional experience of healthcare practitioners often causes a discordance between the methodology of care and the suggestion provided by the CDSS. In such situations, clinical experience repudiates decision support systems in dictating the care path for a patient [26-28]. During such circumstances, allowing nurse navigators to provide thorough information to the patient becomes crucial in the patient's ability to make an informed decision regarding the way further.AI tools can help in estimating urgency, requirement of physical examinations, timings and consultations to auto-plan medication schedule [9]. Disease dynamics in cancer involves a changing course of treatment based on severity or stage of the disease. This necessitates the involvement of a human element in each process to maintain workflow continuity [29].

AI tools require comprehensive datasets that stratify medical, psychosocial and financial aspects of patient information while generating the training datasets for the AI algorithm. This must be correlated with breast cancer, as well as patient characteristics. Often different modalities of care are not locally available; this gap can be bridged by data-collection which fulfils the flow of data across centres and unnecessary double entries of data; sometimes also involving repeat tests, allowing TBs and care coordination to ease the heavy administrative task. Each TB brings the most important pre-determined data points such as TNM staging, prescription for radiation, chemotherapeutic agents or alternative approaches and similar critical data together across systems, and the report contains the most valuable details necessary for analyses and automatic care planning [9-13,19].

Ideally, when response evaluation and toxicities are reported back into the same system and all decision steps are made within the same TB, the learning potential of AI prediction tools become very strong and locally representative [19,26,30,31].

Patient note and AI

Physicians spend up to half of their work day reviewing electronic medical records and data entry [32]. AI based natural language processing systems can now perform as ambient sensors in doctor patient conversations [33], however AI still needs human intervention to categorize essential data pertinent to the patients' current health condition based on the conversation. Conversational assistants cause patient privacy concerns with inability to accurately deduce information [34]. Words represented on the electronic health record can be misinterpreted due to synonym or polysemy of words [35]. Development of medically enabled NLP systems will help target this issue by categorizing words based on context of the note [36].

De-identification leading to missing information

Electronic health records contain sensitive data which needs encryption before being fed into cloud systems for storage or analysis. Although the FDA is encouraging the creation of vast repositories of real world data and real world evidence, these data-sets are de-identified to avoid bias [37]. However, too much information off-loading for the benefit of privacy sometimes causes datasets to lack value in creating personalized treatment models. This occurs because the temporal association of the data may be lost or the institutional guidelines may restrict data sharing on multi-organizational repositories [38,39]. It is therefore important to create utility-preserving datasets with parameters like genetic construct, treatment regimen utilized which allows future review of the dataset for alternative utilization [40,41]. Including patterns of nurse coordinator interventions, the extent of referrals, number of emergency visits or hospital admissions pertinent to breast cancer care in analysis of patient's demand, including patient based questionnaire covering extent of information understanding would be valuable data points to assess co-ordination of data [42].

Barriers in care coordination that can be overcome with time

Although TBs can bring the 3 facets of care together, it is just a starting or reset point in the whole care path of each patient. For fluent care coordination, additional aspects of care coordination need to be addressed along with TB: clear health professional role and responsibilities (leadership and responsibility), transitioning of care (timely communication among specialists, as well as with primary care), access to care (privacy, distance and costs) and financial management (allocation of budget to key elements of care, which may vary based on region [5,9].

In all aspects AI can play an important role, being emotionless in contrast to the patient (all want to be helped the next day), but able to integrate urgency based on cohorts of comparable cases with the same indication, e.g. pain, mortality risk, optimally levelling costs aiming at affordability [26,27]. The planning across different departments and centres will need, however, full data access or still human intervention [28,43].

Most planning tools today only work within one data circuit involving singular fragmented network of either banks or hospital. This is to maintain data security within the limits of consent the patient has given to one data-owner, but also moreover to shut out competition [5,30,43].

Since care coordination is of high interest to the patient itself, most existing tools work with a patient portal connecting to the different data points. Within one network of care providers, this can create communication and care planning, which is more streamlined, however, it does not permit the patient to acquire opinions, exams or treatments faster in neighbouring or out of centre consultations [26,44,45].

Overall, good care coordination during active care can be facilitated by appointing an 'director' coordinator or nurse navigator, centralized data capture, alignment of care plans across centres and regional collaboration networks. Data sharing and analyses can be done creating anonymous data cohorts driving AI decision and predictive risk tools [10]. In case of large distances, telemedicine can be utilized. For financial management, the nurse navigator or special administrative support can be consulted. AI analysis of data can uncover patterns in non-compliance identifying potentially correctable reasons of costs or distance. AI systems can be linked to an electronic medication bottle cap which alerts the healthcare provider each time the pill bottle is opened. AI based learning systems can then provide intuitive feedback in the form of text messages to help in medication compliance [46-49].

Limitations

In the ideal case, the breast cancer care path starts with screening and continues with the correct guidance during survivorship [26,27]. Coordination has to link [50] primary health to specialist care along all the way, but the 'director' role assumes changes in position based on the stage of the disease. Constant communication is essential to bridge the exchange links correctly to the process of seamless follow up of each patient in primary care parallels [2,5]. Instead of the portal being institutional centric, it should be decentralized, web-based and patient centric. Adequate patient education might be required during the initial stages of deployment of the web based application [48]. Care seeking and appraisal is primarily affected by cultural, social and emotional norms that may play a major role in dictating choice of care. Standardizing the emotional quotient of the patients' outlook remains to be a well-known challenge. However, questionnaires like FACT-B have shown that social integration of breast cancer patients shows improved quality of life outcomes [51].

Communication challenges can be overcome by utilizing AI mediated graduated educational tools providing appropriate responses to patients' questions based on the current stage of the cancer. Patient based questionnaire, image based description, short survey interviews or medical records could indicate appropriate information that could be provided to the patient [52].

Symptom management

Suboptimal coordination in cancer care has been shown to be associated with adverse outcomes such as inadequate symptom control, duplicated diagnostic tests, and increased medical errors and health-care expenditures [26,53]. Edwards., *et al*. showed that approximately one third of females with breast cancer had at least 1 comorbidity and presence of comorbidity was associated with poorer overall survival. Care coordination requires diverse specialists owing to high prevalence of comorbidities and medical complexity. In consequence, collaboration with out of network providers may be warranted, resulting in suboptimal care, poor survival, and increased toxicities and healthcare costs [54]. With the increase in the aging population, cancer care has become more complex and comorbidities such as diabetes mellitus, obesity, and cardiovascular diseases have become more prevalent in the general female population [13,55]. Successful care coordination can have an important impact on cancer care outcomes; however, it necessitates effective communication among all stakeholders and information sharing [45].

Sarfati., *et al*. point out that comorbidity management is poorly recorded, although carries a significant impact on cancer care [56,57]. Clarity on the leadership in integrated care here, gets even more complex. Medical oncologists often consult inter-professionally to address the management and monitoring of non-cancer related comorbidities. As a consequence, patients are referred to primary care physicians and/or specialties - thus increasing the fragmentation in care [58]. Medical oncologists often do not feel comfortable in management and monitoring of non-cancer related comorbidities. Therefore, patients are referred to others - thus increasing the fragmentation in care. Bringing a geriatric evaluation and cardiac, diabetes or lung monitoring into the overall care plan from the beginning can improve care quality but the 'director' role needs to be share with continuous communication which makes coordination more complex [55,56].

Barriers in symptom monitoring

Breast cancer care is known for its most complete (national) guidelines, extensive clinical trial network and certified oncology subspecialists (radiology, surgery, etc) and care-teams. Most guidelines incorporate monitoring and response evaluation moments standardizing most care paths. Automated planning of this kind of monitoring does, however, not cover toxicity management. Here the doctor´s consultations and patient education is still essential. We can imagine AI based predictive toolsets to steer tailored prescription based on characteristics of treatment, blood results and symptom scoring also serving toxicity-risk. To our opinion, prescription itself will continue to remain a doctor's act, however more detailed risk profiling can help in deciding upon dose and recovery timings based on AI algorithms early on during prescribing. There are different projects published that show symptom distress, nursing relations and early intervention can be facilitated with computer-supported assessment tools [59,60]. Overall survival benefit is described in metastatic patients using mobile tools to report early during routine cancer treatment [60,61]. However, to implement systematic symptom reporting in daily clinical practice across different departments needs some system of alerts that filter normal values, mild toxicity from severe signs needing urgent interventions, not overloading the care team with normal results eventually missing the severe events [62-64].

Overall, like care coordination, symptom management needs communication across disciplines, data collection over time that permits comparison, and filtering to avoid overload of information. Filters need to be critical putting symptomatic patients effectively back into the grid to be consulted. To keep symptom monitoring manageable, filters are critical in re-directing high-risk patients effectively back into the grid without being erroneously filtered. Scaling reported outcomes based on cohorts of the same type which emphasize the importance of severe signs needing urgent interventions [65]. This step still requires constant human monitoring of the system application to ensure proper functioning.

Patients are eager to communicate, upload and share information, although lack capability to filter the information or translate issues that concern into urgency measures [9,62]. Human intervention here, helped by a chatbot or automated filter tool (like lab values being in normal range) is necessary. Also, clinicians need to adapt and change over time [64]. With the right collection of data on treatment details, as well as patient characteristics, AI can create not only provide preferred treatment choice [17,46] but go the step further with risk prediction tools that can advise dose reduction or delay of treatment regarding neutropenia risk or plan adaptation in radiotherapy anticipating normal tissue damage. These are all ongoing projects that hopefully will shape our future cancer care directions [19].

Symptom monitoring and response evaluation do not only have their place during treatments but during follow-up as well [61,66]. There were more than 3.8 million women with a history of breast cancer living in the US in 2019 and the number is still on the rise. Just by volume, continuous monitoring of survivors is becoming more challenging [27,67]. Effective and organized coordination of care is imperative in continuous monitoring of breast cancer survivors. A significant proportion of survivors experience long-term effects including but not limited to cognitive dysfunction, mood disorders, cardiovascular disease and secondary malignancies [68].

System solutions facilitating continuous feed-back by the patients or primary care providers can play a major role here in early detection of severe late effects or disease recurrence. Moreover, data collection after treatment is essential in any predictive toolkit development aiming disease outcome, taking into account relative risks for late morbidity induced by cancer treatment [9,57]. Compliance to follow-up questionnaires are rarely optimal, however, with on-line monitoring during treatment, patients seem far more motivated to continue to report. This can also be attributed to decreased logistic expenses for the patient and significantly reduces the burden on the healthcare system [61,69]. Moreover, early detection of non-compliant patients on follow-up would be essential to detect treatment failure [70]. Continuation into follow-up modules of this work would set the stage for comparative trials of care models to be meaningful and yield more definitive results about the potential benefit of prolonged care plans, still disputable today.

Adverse effect prediction/monitoring

Adverse effects (AEs) of breast cancer treatment are associated with increased mortality and morbidity, which may persist beyond the treatment period [71]. AEs often cause changes in treatment regimen and can increase the burden on healthcare system. Prediction of AEs therefore have an important role in prevention of poor outcomes related to breast cancer treatment [72].

Current practice focuses on risk stratification with only certain patient factors and biochemical markers and is subject to inter-clinician variability and bias [73]. Advanced predictive models using big data may take various characteristics of an individual and prognostic markers into account to help physicians predict AEs. Moreover, AI-driven prediction tools for AEs can be implemented into EHR, hence, providing real time data. Precise risk stratification using these tools can improve adverse effect identification [74], drug-drug interaction [75] and monitoring in addition to potential modification of treatment [76]. Specific learning models based on overall population data to generate optimal dosing schedules [77] followed by extending the ability of AI to detect the possibility of an AE.AE monitoring involves two components post marketing drug surveillance and individual patient reported symptoms. Several chemotherapeutic agents provided to patients are also based out of recruitment in an ongoing clinical trial, this is due to better genetic correlation of the chemotherapeutic agent and the patient's tumour subtype [78].

Data-mining extensive Electronic health records can provide insights into AEs. and be used to predict effective case based monitoring of AEs [79]. However, proper identification and monitoring of AEs can be difficult [80] coming from different sources, e.g. medication review, follow-up visits, lab tests or patient self-reporting. Utilization of patient-reported AEs or PROMS as a basis can improve timely reporting and patient-provider communication. Electronic patient interfaces for self-reporting have already been implemented in several institutions [81]. Without filtering, however, these tools are fast overburdening f busy care providers [82,83].

Follow-up care

Regular follow -up visit to the hospital along with imaging and requisite examination are essential in the care of patients. Some tools can facilitate workflows, like AI based systems have the ability to detect suspect lesions in mammographic images and can function as a second read or AI prediction applications monitoring of 30 day mortality risk after the administration of chemotherapy [84]. Both are examples of leaving the responsibility to the physicians, but facilitate decision making using the large datasets of comparable cases.

Palliative breast cancer care and AI

Palliative care involves a holistic approach catering to psychosocial and debilitating symptom relief. As an example, patients can be provided with an AI based pain management tool, which can intuitively cater to the current level of pain symptoms in the patient and accordingly provide guided Cognitive Behavioural Therapy to suit the patient [85].

Patients and/or family are searching for answers in different points of time, facing prognosis, however, need emotional guidance and support. Although information is out there, human interaction is essential in positioning end-of -life trade-offs [86].

Mobile health applications deployed provides the advantages of accessibility, symptom tracking, medication summary and a reliable point of contact for patients, however, never replace the contact with the dedicated care team [87].

Limitations of the Study

AI systems may get overwhelmed with data causing self-predicting algorithms running astray due to a software glitch and inherent deep learning capability. This issue must be dealt with cautiously since it would have grievous implications on patient care. Artificial Neural networks are opaque enough, offering very little information about how they arrive at conclusions through hundreds of layers of information once deep learning gets involved. This creates a digital subconscious. Reaching the root cause of the AI\ML problem will involve disintegrating the neural network targeting each nodal decision-making unit, consequently marginalizing patient care during that period. Consent and responsibility continue to remain aspects which still remain to be questionable when AI falls into the equation of patient care [88]. A certain amount of fixed time period is required for the data collection process which is limited to specific patient cohorts in order to generate valuable outcomes on the predictive models.

Conclusion

Breast cancer care requires close communication among different care providers. Often expert opinion of geriatric, endocrine or cardiovascular specialists is needed to balance treatment benefit and toxicity risks. Only few system solutions can go across all these different care settings hindered due to data sharing guidelines.

Shared treatment decisions in TBs bring essential information together for each patient and can guide both care coordination and needed symptom management. Development of AI tools using TB data can improve sequential treatment planning, as well as treatment choice quality, moreover by learning local tendencies, guidelines and resources, tailoring potential will get stronger over time.

AI automated planning can streamline care plans, however a human central organizer for each patient, like a nurse navigator, stays essential in leveraging specific needs, timing, distance and costs.

Patient portals can enable effective symptom monitoring, but information overload is a challenge, demanding filters and constant access. Data collection here can be used to create learning loops of predicting outcome and toxicity if well collected and linked to other clinical data. Because of privacy and competition between providers, most efforts in improvement of quality and outcome are limited to one clinical network.

AI inspires an exciting area of research in breast cancer care. It carries a tremendous potential in streamlining the care delivery and improving patient outcomes by individualizing the breast cancer care. Data management and privacy protection, however, limit development of many tools today. Both patients and care-providers need to be educated about data-sharing risks and translation of information. Human interaction for decision control, as well as emotional guidance stay of key importance in each solution.

Conflict of Interest

The authors declare no conflict of interest.

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