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Improving breast cancer care coordination and symptom management by using AI driven predictive toolkits

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ABSTRACT

Integrated breast cancer care is complex, marked by multiple hand-offs between primary care and specialists over an extensive period of time. Communication is essential for treatment compliance, lowering error and complication risk, as well as handling co-morbidity. The director role of care, however, becomes often unclear, and patients remain lost across departments. Digital tools can add significant value to care communication but need clarity about the directives to perform in the care team. In effective breast cancer care, multidisciplinary team meetings can drive care planning, create directives and structured data collection. Subsequently, nurse navigators can take the director's role and become a pivotal determinant for patient care continuity. In the complexity of care, automated AI driven planning can facilitate their tasks, however, human intervention stays needed for psychosocial support and tackling unexpected urgency. Care allocation of patients across centres, is often still done by hand and phone demanding time due to overbooked agenda's and discontinuous system solutions limited by privacy rules and moreover, competition among providers. Collection of complete outcome information is limited to specific collaborative networks today. With data continuity over time, AI tools can facilitate both care allocation and risk prediction which may unveil non-compliance due to local scarce resources, distance and costs. Applied research is needed to bring AI modelling into clinical practice and drive well-coordinated, patient-centric cancer care in the complex web of modern healthcare today.

1. Introduction

Cancer care is known for its complexity, involving different diagnostic and treatment modalities for one patient. Appointments need to be scheduled across different departments and clinics. In the extensive care path, central coordination often goes missing. Patients get emotionally and physically affected by waiting times and communication errors between care-providers. In the search of continuity and information, many (up till 80% of breast cancer patients in the Western world) opt for a second opinion, invariably making their care path even more complex [1,2].

With new digital solutions, addressing planning and communication, like in other industries (banking, travel bookings etc), are coming into the market, consequently making patients become more demanding for digital solutions in their cancer management as well. Introduction of new system solutions has created huge

traction for investment in the digital health market [3—7]. Cancer care, however, is lagging behind due to its current data complexity.

Care providers face the complexity of multidisciplinary care coordination for each patient [1,2,8,9]. In this paper, we map the current situation of breast cancer management, mirror them to possible future models using artificial intelligence (AI) and the needed research efforts to catch up with digital support used in other non-medical settings also utilizing sensitive data.

1.1. Care coordination

To improve individual care coordination and symptom management, we need to unravel breast care management. As addressed previously, central directors are often lacking, as patients move back and forward between different care providers. To improve flow, a central coordinator (e.g. nurse navigator) can lead, but still needs correct input and capability to adjust regarding medical and patients' needs over due course of time within the restrictions of the current care providers continuum. To capture this in a working model we simplify to 3 facets as follows [1,2,7]:

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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: classical breast cancer care involves primary care, radiology, nuclear medicine, pathology, surgery, medical and radiation oncology. Often genetic, palliative and social counselling is accommodated, ideally united into multidisciplinary teams (MDT) which will be centrally discussed. The MDT brings the 2 facets of clinical medicine and approach to care together, discussing medical needs, evidence-based solutions, as well as specific patient requirements in terms of performance, co-morbidity profile, psycho-social and financial considerations. Today, there are different system solutions to support the MDT being part of the 3rd pillar of care management [11—15] aiding to provide decision support [16—19]. National guidelines are the strong back bone of the current tools and clinical practice. As all references, however, most are based on young healthy cohorts, not always directly translatable to all patients. Integration of AI [19,20] using local data can tailor these tools further according to pertinent patient (genetic) profiles. Similar learning loops with local data could tackle risk of toxicity and availability of care. In many countries ground realities depict, modern drugs, radiation and imaging techniques are inaccessible to all patients.

Approach to care: allocation of treatment and consultations are not only medically driven (timing, sequencing) but also depend on patient's capacity to understand, consent, travel and pay. Communication is needed to bring these into the equation of decision making. Integrating social and financial support systems can improve compliance and therefore indirectly improve outcomes [11,21].

System solutions: Automation tools will have to work in a two-way traffic mode which enables the system to take into account medical and patients' needs; which often interpose each other [11,15,18].

Information technology (IT) can facilitate communication care allocation taking all facets into account, but need to be fed with complete, well-structured datasets to base decision-making upon. In principle, IT models using information of historic cohorts can use AI to learn planning systems to anticipate medical needs, estimate and adjust to risks as well as patient's decision\response facts in specific situations. Ideally, future tools in care coordination should take all the above factors into account, while allocating and guiding patient through their most suitable care path. Ideally, the model focusses on maximizing the combinatorial power of IT processing and the socio-psychological judgement of human director intervention steering coordination [19,22].

Human intervention in this process is essential, bringing both MDT and a nurse navigator to the forefront, becoming the mediator for each individual patient [21—24]. For both AI tools can help in estimating urgency and requirements of physical examinations and consultations to auto-plan care pathway and allocate. However, appointment scheduling can be automated only to a certain extent, since access to agendas and overbookings remains to be handled as a human task. Patient education is essential to keep flexibility and adaptation to unexpected disease and toxicity dynamics [11].

AI tools need large well-structured datasets, ideally bringing the 3 facets together using historic data testing for each patient in the same medical, psycho-social and financial situation generating micro-cohorts for each tailored response. Ideally local availability and cost of different modalities of care are taken into account in the analyses. It will be a challenging task, however, to close the information gaps existing today, created by competition among centres, essentially restricting the ideal flow of information across centres. This consequently leads to double entry of data; repetition of tests. Allowing a centralised platform of IT tools to handle this

information can ease the load on administrative tasks. Nevertheless, each component of the MDT brings the most important data points together across systems and the cumulative report contains valuable details necessary for analyses and automatic care planning [11—15,22].

Ideally when response evaluation and toxicities are reported back into the same system and all decision steps are made within the same MDT, the learning potential of AI prediction tools becomes stronger and locally representative [10,19,22—24].

1.2. Solvable barriers in allocation and timing

Although MDT brings 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 co-ordination need to be addressed along with MDT: clear health professional role and responsibilities (who takes the lead?), 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) in each region [1,11]. We addressed the concept of nurse navigator, who can lead, communicate and assist the patient along the whole care path. This role, however, is a heavily administrative and emotionally oriented duty. As empathic humans, we relate to patients and fall in the trap of translating everything as urgent and important. Computers stay consistent and neutral, moreover stress resistant in these tasks. AI can play an important role, being emotionless and able to compute urgency based on historic cohorts levelling indication, e.g. pain, risk, timing and cost, aiming at affordability [21—27] in data-collection.

Since care coordination is of utmost benefit to the patient themselves, most existing tools work with a patient portals connecting the different data points. Within one network of care providers, communication and care planning can be streamlined, however, it does not permit the patient to acquire opinions, exams or treatments faster in neighbouring or out of centre consultations [12,25,26].

Overall, good care coordination during active care can be facilitated by appointing a nurse navigator, telemedicine, centralized data capture, alignment of care plan across centres and regional collaborative networks. Data analyses can be done creating anonymous cohorts driving AI decision and predictive risk tools [10]. AI analysis of data can uncover patterns in non-compliance potentially identifying correctable reasons of causality [28—30].

1.3. Where to start and end?

In the ideal case, the breast cancer care path starts with screening and continues with the correct guidance during survivorship [22—26]. Coordination tools ideally link primary health to specialist care all along the way. The director role can switch from the general practitioner (GP) to the hospital care-team (nurse navigator) and back. Current solutions have put the directives mainly in the hand of the patients. Clinical practice is in urgent need for better tools to respond to this demand for connectivity and integration. Filtering and triage in allocation of care pertaining to symptoms, prognosis, scarce resources and cost can be helped by computing tools, but can never completely replace the translation in patient care in context of the emotional and physical burden of dealing with a life-threatening disease. Allocation of affected patients after positive screening can fall in the same category, where future AI tools could make a difference after sufficient training to handle patient counselling. 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 emotional

quotient of the patient's outlook remains to be a well-known challenge from screening to survivorship. Care directorship alters from radiologists, GPs to hospital care-teams, but are ideally adequately re-directed to the GPs in the follow-up phase. Here, education is essential from the hospital care team to the patients, as well as GPs to allow the natural follow up of each patient in primary care parallels [1,2].

1.4. Symptom management

Poor care coordination during treatment is associated with medical errors, duplicated tests, lack of supportive care and poor symptom control with high costs as a consequent result [24,25]. Breast cancer patients are seen by diverse specialists and 4 out of ten need communication with pertinent care providers for co-morbidity. Pre-existent chronic disease is associated with more frequent sub-optimal curative treatment, toxicities, hospital admissions, poor survival and eventiually higher cost [10,28]. This care complexity is getting increasingly common in the aging population, along with increasing incidence of obesity, diabetes, cardiovascular disease in the general female population [15,31]. Integrating co-morbidity monitoring into the care plan can make significant difference in final outcome, but very few guidelines exist, and results are poorly recorded [26,32,33]. Most oncologists feel uncomfortable taking over the chronic disease care plan during cancer treatment. Moreover, because elderly women with co-morbidity are often excluded from trials, evidence-based treatment choices are based on healthier cohorts and therefore are difficult to translate. Bringing a geriatric evaluation and cardiac, diabetes or lung monitoring into the overall care plan from the very beginning can improve care quality but makes coordination more complex [31,32].

1.5. Solvable barriers in symptom monitoring

Breast cancer care is known for its principally complete (national) guidelines, extensive clinical trial network and certified oncology sub-specialists (radiology, surgery, etc) and care-teams. Most guidelines incorporate monitoring and response evaluation methodologies standardizing care paths for early versus advanced disease including specific drugs, for example dose related cardiac testing. Automated planning of this kind of monitoring does, however, not cover toxicity management. Risk of toxicity is related to the pharmacodynamics and accumulation of different treatments over time, but moreover dependent on the condition, age and co-morbidities of each patient. To tailor treatment based on expected efficacy, as well as risk of severe side effects is a challenging arena. AI models based on historical datasets start to unravel risk prediction, however big data is needed here to demistify multiple variables converging to medication management.

Today, both prescription and timing are crucial in the doctor's consultations and patient education. In the near future we imagine AI predictive toolsets driving tailored prescription based on characteristics of treatment and the patient, blood results and symptom scoring. To our opinion, prescription itself will stay a doctor 'act, however more detailed risk profiling can help in deciding upon dose and recover timing parameters.

Different projects are published showing improved symptom management and survival benefit by the use of computer-supported assessment tools [34–36]. The time gets ripe to use these data in AI driven predictive tools [24–26]. However, implementation of systematic symptom reporting creates a direct data overload, especially while reporting across different departments. To keep symptom monitoring manageable, filters are critical which can redirect symptomatic patients back into the grid to be consulted. Scaling reported outcome among cohorts of the same type with emphasis on indentifying severe clinical signs needing urgent interventions [37–39].

Patients are eager to communicate, upload and share information but lack capability to filter or translate issues that are of utmost importance during an urgency [11,37,39]. Human intervention here, helped by a chatbot or automated filter tools (like lab values being in normal range) are potential intermediates and are well accepted by patients [22,23]. Adaption of automated tools by clinicians, depend on quality and pressure of volume/time which is highly variable and carries a changing landscape over time [39].

1.6. Who does what?

Symptom monitoring and response evaluation not only have their place during the various treatments but also during follow-up [40,41]. Clinical monitoring of all breast cancer survivors is becoming impossible due to the huge volume (expected over 20 million in US by 2026) and adoption of automated follow-up [41]. Most women return to GP follow up at end of treatment. Many women do, however, face persistent effects (e.g. depression, pain, unemployment), additional risks (e.g. cardiovascular, second malignancies) after treatment. System solutions facilitating continuous feed-back by the patients and GPs can play a major role here in early detection of severe late effects\complications or disease recurrence. Moreover, data collection after treatment is essential in any predictive toolkit development aiming at disease outcome, taking into account relative risks for late morbidity induced by cancer itself and the treatment [11,33].

Future AI driven risk prediction for GPs, would help to decide upon referrals back to the hospital and distinguish risk of late effects versus recurrence. Digital tools can help educating both survivors and GPs as health promotion (e.g. diet, physical activity) and accurate coordination of care (e.g. identification of providers of follow-up care) can have a significant impact on secondary medical service consumption, quality of life and return to working and living a normal social life [26].

Compliance to follow-up questionnaires are rarely optimal, however, with the current on-line monitoring during treatment, patients seem far more motivated to continue to report after care services [40]. Continuation into follow-up modules of this effort would set the stage for comparative trials of care models to be meaningful and yield more definitive results about potential benefit of prolonged care plans, still disputable today.

1.7. Cautions

For computers thrombopenia can be a common factor as distance to the hospital, the medical trade off in weighing factors contributing to risk is an art learned over many years of training. To learn a model to accomplish the same needs time and a lot of experience (=data) as well. AI systems may get overwhelmed with data assuming self-predicting algorithms running astray due to a software glitch. This issue implies continuous monitoring of the model implemented in clinical practise since it can lead to grievous implications on patient care. The combination of nurse navigator and auto-planning, as well as daily checks of auto-filtered reported tolerance in a spread sheet are easy control measures to catch unexpected exceptions. Thresholds to alter and double check need to be low for appropriate detection. Because IT tools never sleep, care teams need to organise correct 24 h shifts to respond to alerts, moreover they have to educate patients in what to do with early symptoms [22,23].

In general, 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 problem will involve disintegrating the neural network targeting each nodal decision-making unit consequently marginalizing patient care during that period. 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. With the increasing computing power of today, this is expected to be overcome soon. However, running the standard care protocols and call-ins for extra consultations in parallel is still needed today. Quality care will always need the combination of human intervention of deciding upon the direction and the fast computing model mapping the complex forest of risk factors to navigate within.

2. Conclusion

Breast cancer care coordination and symptom management need close communication across the different care providers including imaging, pathology, genetic and treatment experts, as well as primary and supportive care providers. Often expert opinion of geriatric, endocrine or cardiovascular specialists is needed to balance treatment benefit and toxicity risks in the context of co-morbidity determining toxicity risk. Only few system solutions can go across all these different care settings unhindered due to data sharing guidelines.

Shared treatment decision in MDTs brings essential information together for each patient and can guide both care coordination and needed symptom management. Development of AI tools using MDT data can improve sequential treatment planning. When designed for assessment of treatment choice quality, it can create the essential data collection for AI learning loops embracing both needs.

Clinical medicine and patient approach facets along with AI automated planning can streamline care plans, however a human central organiser for each patient, like a nurse navigator, stays essential in leveraging specific needs, timing, distance and costs.

Patient portals can facilitate symptom monitoring however, filtering is needed to avoid information overload of the care team. Data collection here can be used to create learning loops of predicting outcome and toxicity. Because of privacy and competition between providers, most efforts in improvement of quality and outcome are currently limited to one clinical network.

AI opens an exciting research field in breast cancer care management. Facing tremendous increase in the volume of patients, each with specific traits and risks, we see primordial potential in streamlining agendas and securing continuous follow-up, while constantly tackling associated data collection in a secure environment. AI driven computing risk tools for tailored treatment are an inseparable entity in the future of breast cancer care continuum in the coming decade.

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