Future perspective of heart failure care: benefits and bottlenecks of artificial intelligence and eHealth

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“eHealth and AI hold great potential in the clinical management of patients with HF and will result in a paradigm change for the treatment of these patients.”

Tweetable abstract: #eHealth and #ArtificialIntelligence (AI) bring new possibilities for #HeartFailure (HF) care. We elaborate on potential benefits of #AI in #HF and highlight important bottlenecks for its implementation. #Editorial #Cardiology.

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Heart failure care in 2030

Mrs Smith is a 72-year-old heart failure (HF) patient. Her symptoms include dyspnea on exertion, edema of the lower limbs and weight gain over the past 2 weeks. Worried about her worsening condition, she opens the doctor-at-home app on her smartphone and performs a health check (including the novel bioimpedance and ECG based congestion finder via her smartwatch). The app also collects data from the patient's electronic health record through a secure connection. The doctor-avatar of the app asks the patient for other symptoms, lifestyle and anxiety, and a point-of-care blood and urine investigation is incorporated. The app concludes that the patient is decompensating, and the doctor-avatar recommends the patient to double her diuretics and check-in again tomorrow. The adjudicated informal caregiver of the patient (in this case, her daughter) is notified about the situation by the system through a text message. Based on these clinical parameters and a recent proteomic signature from a drop of blood, sophisticated machine learning algorithms further advise that this specific patient benefits most from increasing the dosage of angiotensin receptor–neprilysin inhibitor in combination with sodium-glucose co-transporter-2 (SGLT-2) inhibition after recompensation instead of beta-blocker and the app sends a new recipe to the pharmacy, which delivers the medication to the patient's home. After recovery from the current exacerbation, the app classifies the patient as being at 'high risk' of sleep apnea (based on her nightly heart rate, breathing pattern and SpO2 values measured by her smartwatch). The system schedules an in-home apnea-test. If the test indicates sleep apnea, a digital consultation with the pulmonologist is scheduled. The patient's treating cardiologist may monitor the current situation and therapy changes via the patients' dashboard, but, importantly, is only notified by the app if concrete action by the cardiologist is needed. The latter is only the case if there is uncertainty by the app about the correct treatment decision.

This hypothetical case demonstrates the potential of implementing artificial intelligence (AI) and eHealth within HF care. Although this may sound futuristic to some, current cardiology urgently requires such applied innovations in the near future to keep up with the growing demand for healthcare. Within 5 years, more than 5 million people will suffer from HF in north-west Europe alone [1]. Considering the intensity of care and the number of hospital admissions for HF and associated comorbidities [2], this portends an untenable situation with unsustainable

healthcare costs. This situation is further exaggerated by the expected shortage of healthcare workers to deal with the increasing number of patients with chronic diseases, including HF [3]. Fortunately, the depicted possibilities of eHealth combined with AI are expected to reduce up to half of the labour in healthcare [4], and potentially even more. In addition, interest in AI in healthcare is growing exponentially, market shares skyrocket and institutions are willing to invest in AI development and application [5]. Therefore, this editorial elaborates on promising benefits of AI in HF and highlights important bottlenecks for its implementation in clinical practice.

Where cardiology can benefit from AI

Precision medicine

Precision medicine refers to specific treatment for individual patients based on any type of profiling – either genetic, molecular, clinical or a combination of all of them. Its goal is to optimize efficiency and benefit of patient management on an individual level by predicting which patient will benefit most from specific (combinations of) drugs or therapies. With an increasing individual profiling, through, for example, proteomics or metabolomics, AI is needed to handle the extensive amount of ‘big-data’ and to enable precision medicine approaches. Unsupervised approaches – in other words, finding patterns in the data without upfront hypothesis – have been successfully employed to dissect the heterogeneous HF population into clusters of patients with common pathophysiological ground, clinically different outcomes and potentially a more predictable response to therapy [6,7]. Supervised approaches – in other words, classifying patients into predefined groups – have shown to be able to segregate ‘responders’ from ‘nonresponders’ to specific HF drugs [8]. Although promising, prospective validation of these precision medicine approaches is required but lacking. To move forward, AI-derived clustering or classification on data from large randomized clinical trials should be promoted. Also, AI-derived phenotyping of -omic type data can discover new drug targets that can be further investigated in pre-clinical research. Most importantly, AI-based hypotheses must be prospectively studied in sufficiently large (e.g., registry-based) randomized controlled trials. Only then, AI-algorithms can classify patients to promote the best possible individual therapy based on multi-dimensional data-input in the future. Simultaneously, AI-systems will learn from every new patient to improve its classification algorithm, resulting in a self-learning system to further enhance treatment response prediction.

Decision support & value-based healthcare

Decision support systems have been used in healthcare for several decades. Such systems are designed to improve healthcare by providing targeted clinical knowledge (such as guidelines), patient information and other health information [9]. Particularly in our rapidly evolving field of new knowledge, rules, drugs and interventions, the use of decision support systems can improve the currently very poor [10] adherence to guidelines and implementation of new advances. Still, current decision support systems are limited by mainly manual data input. AI could overcome this issue by recognizing data and automatically providing the input variables needed in decision support systems. Moreover, AI will enable much faster and more accurate guideline adherent diagnostic and therapeutic decision making. Currently, decision support mainly targets healthcare professionals, but with increasing accuracy, it will gradually involve patients (with HF and other diseases) directly.

Disease-management is another aspect that will benefit from AI. Healthcare is increasingly reimbursed by quality rather than quantity measures (value-based healthcare) [11]. For a department or a hospital to improve quality of care, data-driven decision making is highly attractive. AI systems cannot only predict outcome on a patient level but can also predict which changes in overall disease-management strategies will lead to better cost–effectiveness.

Comorbidities

Medicine has shifted from a holistic approach as practiced by Hippocrates to increasingly specialized subspecialties. Within the field of cardiology, we currently have HF specialists alongside electrophysiologists, imaging specialists and interventionalists. At the same time, multimorbidity is becoming more prevalent [12], forcing patients to deal with many different care providers. Communication between them is often insufficient. Additionally, the interplay between multiple diseases and guidelines is complex. Although the redirection of care back to general practitioners (GPs) can be appealing for patients and may even reduce costs, GPs may also struggle to deal with each individual (co)morbidity and moreover the combination of them. AI has the capacity to process all necessary information and to combine recommendations from multiple guidelines. Hence, AI can support care for multimorbid patients in a holistic yet modern way. Finally, AI can help detect the development of new comorbidities by evaluating

characteristics of patients over time. Early detection may support a timely start of therapy and may even prevent disease(s).

Patient involvement

Patient participation in healthcare has gained more attention over the years, as it can improve the quality of care and patient satisfaction [13]. Implementing AI (tools) provides an excellent opportunity to enhance this further. An AI module that, without the intervention of a human healthcare provider, investigates symptoms together with the patient and makes a new treatment plan, can be seen as a new form of self-care. Patients become more independent and get responsibility to the extent that they want to have. Patients can consult the doctor's avatar (as in our described case) any time at the discretion of the patients. When combining this with education modules, patients can gain more insight into their disease to further enhance self-care [1]. Of which the latter has been proven to improve outcomes [14]. As a result, the burden on healthcare may decrease to enable sustainable care in the future.

Bottlenecks

Although interest in AI in healthcare is growing exponentially, several bottlenecks need to be considered before AI can be implemented. AI needs a reasonable amount of data to reach reliable conclusions. On the one hand, information collected in current research usually focuses on specific questions only and reuse of data is often limited. On the other hand, a large amount of clinical data is stored in electronic health records (EHR), but they are primarily stored as natural language only. This way of data storage leaves two options for AI implementation. The first option is to manually convert data into computer interpretable labels, which is very time consuming and thus limited. The other option is using AI's natural language processing abilities to analyze the current data in EHR's directly. This technique is in development now, and the results are promising [15]. However, important information is often lacking, definitions are imprecise and data structure is often too complex (storage of data at too many different places) to fulfil the requirements for implementing the above-mentioned AI applications in the clinics. This clearly shows that a lot can be gained in how we deal with data in patient files. To allow AI applications to support and be part of healthcare, we should strive to work as little as possible in natural text but rather in computer interpretable and clearly defined labels.

Secondly, AI models developed in one patient group cannot be directly applied to other patient groups. The models and clustering can vary greatly between countries or even regions. This emphasizes even more that standardized data in EHR's are crucial for AI models to automatically retrieve data that apply not only to specific patient groups and/or regions.

Thirdly, development of models – independently of their purpose – usually rely on existing data, even if prospectively collected, whereas prospective validation is very limited. It is sometimes available for prognostic prediction models, but it usually remains unclear how such models should influence clinical decision making. In fact, there are no prospective studies showing that knowing the prognosis of patients has any impact on patient management and that it improves outcome. Even more so, there is no single study – to the best of our knowledge – that prospectively investigated models for individual therapeutic decisions based on AI.

In addition to technical and scientific issues, financing of care provided by AI is also an important issue. The current health insurance policies (in most countries) do not directly refund computer-based or automated decisions. For instance, a physician must have physical or telephone contact with a patient for a treatment to be reimbursed. Given the increasing pressure on care, this needs to change. In the future, medical decisions will be made by AI without the direct intervention by healthcare professionals. Therefore, insurance companies will have to engage in discussions with hospitals/doctors and developers in the coming period to determine how these automated treatments will be reimbursed. Without reimbursement, the development of eHealth in healthcare is hindered significantly. Recently, however, progress has been made in the USA in this area, with the first AI reimbursement option in healthcare being approved by the Centers for Medicare & Medicaid Services [16].

Finally, adoption of these new techniques by both patients and caregivers needs attention and will take considerable time. Following the algorithm of Rogers, approximately 50% of people will be a 'late adopter' or even a 'laggard.' This means they will be skeptical or even have an aversion against new innovations. Unfortunately, HF patients are likely to be late adopters considering their (on average) advanced age and lower social status [17]. Stakeholders in the field should be aware of this and should address these issues to ensure delivery of these technologies into the mainstream.

Beside these bottlenecks, ethical aspects of course also need to be considered [1] but are, however, beyond the scope of this editorial.

Conclusion

eHealth and AI hold great potential in the clinical management of patients with HF and will result in a paradigm change for the treatment of these patients. In fact, there will be a shift to much more patient self-care, supported by these novel technologies, promoting remote care not only in times of a pandemic. They will also enhance the exchange and use of meaningful information. However, essential steps are required at many levels for broad implementation. This includes sufficient and reliable data provision to AI-systems, prospective testing of AI prediction models for implementation in clinical practice, adjustment of care processes and appropriate reimbursement, consideration of ethical aspects and last but not least, acceptance by both patients and caregivers.

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