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PERSPECTIVE

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'Without data, you're just another person with an opinion'

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ABSTRACT

Introduction: Given the recent impressive digital transformation worldwide, the importance of data has reached a new dimension. It is, therefore, provocative to ask whether data can save healthcare systems from bankruptcy.

Areas covered: We reviewed published examples in the search for the evidence on how the growing amount of data could change the way we used to assess the value of healthcare technologies, ensuring a more holistic approach in the decision-making process while reducing the waste in the healthcare.

Expert opinion: The growing amount of data will continue to provide a multitude of valuable insights that can save healthcare systems from bankruptcy. Electronic medical records, IoT, wearables, and mobile applications generate constant data streams that can be utilized endlessly thanks to methodological advancements such as SNA, unsupervised and supervised machine learning, and natural language programming. However, interoperability across these multiple data sources still pose a challenge for the future development of data-driven healthcare. Already today however, decision makers can utilize Big Data to develop conditional coverage schemes for very expensive and complicated health technologies suitable for personalized healthcare. More advanced payers may utilize even data analytics even further and develop AI-based pricing schemes.

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1. Introduction

Faced with the dual challenges of an aging society and escalating costs of medical innovations, the pressures on healthcare budgets have increased exponentially. According to the available estimates, the current annual growth rate of medical expenses through 2022 will be almost twice as high as that during 2013 to 2017 [1]. In addition, a scarcity of financing resources has clearly led to a transformation in the healthcare sector. There are a number of different trends that indicate how the healthcare system is changing in response to financial and organizational hurdles.

First, the limited budgets available for healthcare spending have influenced to the introduction of new concepts such as 'personalized medicine'. The evidence-based decision making coupled with individualized approach to healthcare supports budget holders with their strive for optimal allocation of scarce resources. Instead of attending solely to the consumption of healthcare services, payers are growing more interested in health outcomes and the quality of medical services. As a result, the healthcare financing model is changing from pure quantity to a quantity–quality matrix [2]. To accommodate that change, not only are more data needed but different types of data are required as well to better inform the pricing and reimbursement processes regarding new innovative health technologies [3].

Second, the scarcity of financial resources has triggered a more holistic approach regarding the process of introducing new health technologies [4]. In the quest for equality and fairness, the involvement of multiple stakeholders in the decision-making process has become a new norm [5].

There is a growing understanding of the need for the engagement of both the patients and public opinion in the decision-making process regarding the allocation of scarce healthcare resources. As the result of multiple voices being more prominent in the pricing and reimbursement discussions, new perspectives are shaping the definition of the value of health technology. A more holistic picture of the healthcare system is emerging, which is not dependent on just one but rather multiple attributes and viewpoints. Therefore, the multi-criteria decision-making model is gaining more attention [6].

Third, the scarcity of healthcare resources has led to the pursuit of new ways to identify optimal budget allocation [7]. Some estimate that over treatment, failure in care coordination, failure in care process execution, and administrative complexity account for up to 20% of the healthcare budget [8]. The awareness of healthcare spending has gathered momentum. For instance, the ClearHealthCosts initiative collects pricing information directly from patients to compare out-of-pocket payments across different healthcare providers. As a result, it produces transparent information about the differences in healthcare pricing for both patients and payers. Similarly, Health Analytics India investigates costs data across the country to inform the general public about the performance of healthcare systems [9].

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[i]Quote from W. Edwards Deming

Article Highlights

- The scarcity of financing resources has clearly led to the transformation of the healthcare sector.
- Health data are growing at a 48% annual rate. The challenge is how to find new ways to convert this flood of structured and unstructured data into meaningful information that supports the optimal allocation of scarce healthcare resources in the era of aging societies.
- Advancements in descriptive, predictive, and prescriptive data analytics may contribute towards further development of personalized medicine and the implementation of holistic mind-sets while facilitating the quest for the optimal allocation of limited healthcare resources.
- Data analytics will grow in importance with algorithms based on traditional predictive modelling or AI along with machine learning.
- Decision makers can utilize Big Data to develop conditional coverage schemes for very expensive and complicated health technologies suitable for personalized healthcare. More advanced payers can utilise data analytics even further and develop AI-based pricing schemes as well.
- New healthcare models based on health data generated through multiple data streams will be patient centric. The patient will become the centre of the financial process.
- Data driven clinical decision support tools enable the discussion of Big Data's contribution to the search for the optimal allocation of healthcare resources at both the national and local levels.
- Digital innovation is moving so fast that healthcare professionals have difficulty digesting the changes and coping with them. As a consequence, this may become a barrier to faster adoption.
- Interoperability and information exchange standards are evolving to address Big Data's future. Nevertheless, today more than 80% of medical information remains unstructured and hard to process.
- Security, data privacy issues, and cybersecurity represent increasing setbacks that need to be addressed in the years to come.

As a result, pressure is being placed on patients and clinicians to ensure more rational use of limited healthcare resources.

Interestingly, there is a 'common denominator' for all three trends leading the transformation of healthcare systems – data. Given the recent impressive development of digital transformation, the importance of data has reached a new dimension. Some estimate that in the healthcare sector, the growth rate of data is currently at 48% annually. The challenge is how to find new ways to transform this flood of structured and unstructured data into meaningful information that supports the optimal allocation of scarce healthcare resources.

The objective of this paper is to explore how new streams of data will contribute to further the transformation of the healthcare system across different jurisdictions. In particular, we address the question of how the growing amount of data will change the way we assess the value of healthcare technologies, ensuring a more holistic approach in the decision-making process, or in the search for waste reduction in healthcare.

2. Why data are transforming the healthcare system?

According to the Economist, it is not oil but rather data that represent the key resources of the 21st century [10]. Professor Klaus Schwab, Founder and Executive Chairman of the World Economic Forum, proclaimed that we are entering the era of The Fourth Industrial Revolution, 'characterized by a range of new technologies that are fusing the physical, digital and biological worlds, impacting all disciplines, economies and industries, and even challenging ideas about what it means to be human'. There are seven technologies that are expected to have the greatest impact on the future development of industry [11]. Among them are Big Data, artificial intelligence (AI), autonomous vehicles, custom manufacturing and 3D printing, the Internet of things (IoT), robots, and social media. The concept of Big Data seems to be a key driver of transformational change. Similar findings have also been reported in 'Embracing Healthcare 4.0' issued by Siemens Healthineers in 2019 [12].

The concept of Big Data is defined by four different characteristics that the data have to incorporate: velocity, variety, volume, and veracity [13].

Given these recent advancements, it is justifiable to ask how the growing amount of data will transform healthcare and, more precisely, how it will impact the future development of value-based pricing, the transparency of decision making, and healthcare waste reduction. In the quest for answers, the distinction among three types of health data analytics should be noted: descriptive, predictive, and prescriptive. While the first focuses on 'what happened', the second addresses 'what will happen', and the last searches for 'what should be done'. We structure our further discussion into three sections corresponding to these three types of data analytics.

3. Big data descriptive analytics

Descriptive analytics capture a basic type of data analysis. In simple terms, this analysis assesses past events. It can, for instance, be a study of statistical data regarding the utilization patterns of healthcare services or a study of epidemiological data about the incidence and prevalence of different diseases [14]. The potential of Big Data in the context of descriptive analysis can be explored in social network analysis (SNA). Although it originates from the social sciences, there are a growing number of examples of its use for 'knowledge translation and transfer' in the healthcare sector as well [15].

SNA studies the structure of relationships between entities. It measures and maps the pattern of connections between individuals and groups. It describes network density (number of actual ties/number of potential ties) and node centrality (a property of a node's position in a network; the structural importance of a node) [16].

There are some studies that already illustrate the potential of SNA looking at patients' and clinician's preferences [17]. With the emergence of Big Data, it can, therefore, be an attractive tool for the transformation of the healthcare system, which can improve the understanding of different stakeholders' needs and introduce more holistic decision making.

Thus far, SNA has been adopted mainly to study offline social networks. It has been used to analyze the impact of communications across healthcare professionals on patient safety as well as quality outcomes [15]. In one particular study, the Organizational Network Analysis questionnaire was used to study the impact of nurse communication patterns on patient satisfaction, self-care, and symptoms management in US settings. It was found that denser and less hierarchical networks correlate positively with patient outcomes [18]. In another study, key drivers of patient choices were explored. This study of networks of connections established by 47 asthma patients in Australia revealed how patients chose to manage asthma; specifically, the reasons why they chose a given treatment pathway [19].

There have already been attempts to utilize SNA in the assessment of patient preferences revealed on social media. For instance, one study investigated the kind of valuable insights SNA could generate into patients' emotional, instrumental, and informational needs to develop psychosocial support or social support for oncological patients [20]. Another application of SNA in the era of Big Data relates to a study of clinician preferences revealed through an analysis of more than 100 million medical claims in Brazil. The data analysis covered how physicians interacted with each other concerning patients' journeys in the healthcare system and the criteria for patients being remitted from one physician to another [21]. A similar approach was utilized to study pain medication prescription patterns revealed in the Healthcare Organization Services (HCOS) dataset between the years 1996 and 2017. The application of SNA provided evidence that affiliation to the same organization and affiliation to the same hospital had a significant impact on the prescription patterns. The results of such studies indicate that SNA can help establish the key drivers of clinician choices and, at the same time, provide important insights into the process of the diffusion of innovations across physician networks [22].

Although SNA is best utilized to reveal preferences and, as such, provide insights into decision-making processes, there are other interesting applications of SNA in the era of Big Data. It can be useful in the search for optimal allocation in healthcare as well. An example is the age- and gender-specific comorbidity relations' model based on the Austrian national medical records. Both outpatient and inpatient data of more than eight million patients were studied to establish age- and gender-dependent network structures to address the question of how new diseases are acquired as comorbidities of already existing ones [23]. The network analysis enabled a forecast of the burden of diseases over the next eight years in the total population. There are some examples that explore SNA in the field of infectious diseases. Combining molecular epidemiology and SNA may enhance computational capacities and boost the development of new techniques. As a result, it has the potential to improve the understanding of how pathogens are spread in a community and predict further epidemic developments much faster [24].

4. Big data predictive analytics

A more advanced form of data analytics is predictive analytics. It aims to assess the likelihood of certain events happening in the future. Available examples indicate its usefulness in the development of a personalized approach in the implementation of health technologies in clinical practices. For example, the analysis of the cohort of 1,294 patients included in a chronic disease management program enabled the prediction of in-control and out-of-control hypertension. As a result, personalized hypertension medication recommendations could be elicited; one way to ensure better effectiveness of a chosen treatment at an individual level [25].

Predictive analytics not only introduces a personalized approach for how a given disease should be treated but also for how it can be prevented. An example is the study of diabetes risk factors conducted on retrospective medical records of 4.1 million individuals in US settings (Population-Level Prediction of Type 2 Diabetes From Claims Data and Analysis of Risk Factors). The analysis included as many as 42,000 variables. The study established an enhanced set of predictive variables that extended a list of 21 classic diabetes risk factors with new ones such as chronic liver disease, high alanine aminotransferase, esophageal reflux, and a history of acute bronchitis. The new model increased the prediction of positive values (PPV) by 67% and the area under the curve (AUC) by 6.6% compared with the standard model. The findings enable a more accurate diagnosis and, consequently, more effective prevention of the costly consequences of diabetes. The study clearly shows how predictive analytics may redefine the value of treatment by providing relevant insights into disease factors and enforcing changes in the clinical pathways. The results from Razavian and colleagues are already deployed at Independence Blue Cross for the allocation of disease prevention measures.

The above examples are not unique. There are plenty of other cases that indicate the clear value of electronic medical records for the development of a personalized approach to healthcare. Interestingly, other adaptations of predictive analytics with the use of digital data sources are emerging as well. An example is the case of the Personalized Allergy Symptoms Forecasting System (PASYFO). It is a free application available on mobile developed by an international group of scientists from Siauliai University, University of Latvia, Finnish Meteorological Institute, and the Medical University of Vienna. More than 10 years of data have been utilized about the dispersion of air allergens (mainly pollen) and its impact on health adjusted to personalized information on allergy symptoms. PASYFO is an example of how continuous health monitoring among patients can be successfully implemented with the support of digital health solutions.

In this era with growing amounts of health data, predictive analytics have the potential to become tools for the optimal allocation of healthcare resources as well. The data from electronic medical records can be successfully utilized for clinical decision support purposes. An example is the introduction of the Epimed ICU Performance management system. Based on the medical records of 2.5 million adult patients, a decision support algorithm was created. The algorithm predicts the length of ICU stays taking into consideration the clinical characteristics of a given individual collected on the first ICU day. The study of 71,002 admissions in 78 ICUs at 51 hospitals in Brazil found that there was a clear association between Epimed's implementation and efficient resource use and hospital mortality. Furthermore, the launch of that clinical decision system introduced an opportunity for benchmarking across healthcare providers and continuous data collection on trends on bed occupancy and resource use for further improvement in the healthcare system [26].

The role of predictive analytics in the search for optimal allocation can be exemplified in the hospital readmission policy as well. Denmark, England, Germany, and the US have already implemented specific financial penalties for hospital readmissions [27]. Consequently, healthcare providers are increasingly interested in opportunities using Big Data that can help them more efficiently target patients at higher risk of readmission. There are already some algorithms developed in this respect. For instance, the most recent Baltimore score (B score) was developed based on 16,649 discharges from three US hospitals. Among 8,000 possible variables, 382 predictors of readmission were identified. The area under the receiver operating characteristic curve (AUROC) for an individual was 0.78 (95% CI, 0.77 to 0.79) at the time of discharge, which was much better than other algorithms such as the HOSPITAL score 0.63 (95% CI, 0.61 to 0.65), and the modified LACE score –0.66 (95% CI, 0.64 to 0.68; $P < .001$) [28].

5. Big data prescriptive analytics

Prescriptive analytics are the most advanced form of data analytics that help address the question: what course of action is likely to produce the maximum benefit given the observed conditions? AI is a key driver in the adaptation of prescriptive analytics for healthcare.

Multiple efforts are underway to enable AI-based analytics [29]. Already, one can read through millions of records and medical data to detect links or similarities between biological characteristics and diseases, and doctors can now discover problems that remained imperceptible in the past. Thus, AI is enhancing human intelligence and allowing us to make decisions faster and with better accuracy [29]. As such, AI can be regarded a valuable tool to address the challenge of optimal allocation in the healthcare sector. An example is the case of the AI-empowered clinical decision support alert system for medication errors (MedAware). Not only does it use predefined rules iteratively derived and refined from prior data mining analytics, but it also has self-learning and self-adaptive capabilities, which allow it to automatically and continuously search for the patient- and institutional-specific novel outliers, which could represent medication errors or problems. It was tested on a sample of 747,985 patients who had at least one outpatient visit between 1 January 2012, and 31 December 2013, in the US setting. MedAware generated 15,692 alerts with 76.2% considered clinically valid. Another example is how AI can improve the process of the allocation of resources based on clinical field trials thanks to early and accurate assessment of the efficacy and safety of new health technologies. There are already AI solutions that provide visual confirmation of medication ingestion. Using facial recognition and computer vision, software algorithms identify patients and the drug and confirm ingestion. Such technology has been used, for instance, among 28 patients diagnosed with ischemic stroke receiving anticoagulation treatment. In a non-randomized sub-study of a phase two trial of the α7 nicotinic receptor agonist (ABT-126) in subjects with schizophrenia, the difference between the AI platform and study staff monitoring was 17.9% (95% CI −2 to 37.7; $P = .08$) [30]. Thanks to a guarantee of 100% compliance with treatment, a study sponsor can plan a given clinical trial accurately and organize the clinical program in a fast and effective manner.

There are some spectacular examples of how machine learning, convolutional neural networks, and natural language processing can redefine the approach to personalized healthcare as well. For instance, Ginger.io is revolutionizing the treatment of mental disorders. It is a mobile application designed for multiple health problems, from stress and anxiety to depression. Thanks to its connectivity, healthcare providers are notified of any changes in behavior in their patients in real time. AI enhanced personalized healthcare has provided support for a major gain in the field of personalized diagnostics as well. For example, an experiment comparing the AI algorithm with a deep learning convolutional neural network (CNN) with 58 dermatologists from 17 countries indicated that the latter accurately detected an average of 86.6%, while the CNN accurately detected 95% of the melanomas. Arandjelovic et al., by contrast, demonstrated the improvement of the accuracy of Stage II colorectal cancer prognosis with the adaptation of machine learning on data generated from a sample of 180 patients who underwent surgical resection, with a follow-up of 11.5 years [31].

6. Conclusion

In conclusion, the growing amount of data will surely transform healthcare systems. There are already multiple examples available that highlight how descriptive, predictive, and prescriptive data analytics can contribute toward further development of personalized medicine and the implementation of holistic mind-sets while facilitating the quest for the optimal allocation of limited healthcare resources. Electronic medical records, IoT, wearables, and mobile applications generate constant data streams that can be utilized endlessly thanks to methodological advancements such as SNA, unsupervised and supervised machine learning, and natural language programming. However, interoperability across these multiple data sources is a key success factor for the future development of data-driven healthcare.

7. Expert opinion

The objective our article is to explore how new streams of data will contribute to the further transformation of the healthcare system. In particular, we focus on how the growing amount of data will change the way we assess the value of healthcare technologies. The underlying intention with the presented examples was to address the question of how to balance access to new innovative healthcare technologies while sustaining the affordability of healthcare at both the local and national levels [32].

One of the key challenges with the value assessment of the innovative healthcare technologies is to ensure their connectivity. The future of medical care depends on the combined diagnostics, medical devices, e-health/m-health, and pharmaceuticals which are very often named as complicated health technologies. Health policymakers should, therefore, focus on the adequate and timely assessment of effectiveness and cost-effectiveness of such integrated health technologies. Next to well organized RCTs, clinical and resource data from real practice (real-world data, RWD) are needed [33]. Although some still believe that these data needs should be considered sequentially (RCT first and RWD later), we expect that both types of data will eventually be pooled in network meta-analyzes and even in more advanced predictions. Therefore, there is growing interest in methods that combine RWD from Big Data sources with RCTs to obtain reliable evidence for the HTA processes. Thus, data analytics will grow in importance through algorithms based on traditional predictive modeling along with machine learning. Ideally, these methods, subsequently, may be used to support clinical decisions as well as the new funding models such as pay for performance or pay for health outcome. In essence, data analytics should be perceived as a support tool in the search for the optimal allocation of limited healthcare resources by enabling new methods that combine evidence from different data sources as well as enabling new healthcare financing schemes.

Indeed, the growing amount of data can contribute toward healthcare transformation into more holistic financing models. The earlier examples highlight the possibilities of data collection on different stakeholders' preferences that can be regarded as valuable input into decision-making processes; the greater the engagement of multiple groups of interest, the greater the transparency and the acceptance of difficult choices. Therefore, healthcare policymakers should encourage patients, in particular, to contribute to the pricing and reimbursement processes by sharing health records and data about their experiences with healthcare services [34].

Surveys show that personal data have an increasing value on the market. Already, there are initiatives that encourage patients to share their DNA data. Still, cybersecurity threats are increasing dramatically in the healthcare sector as well. For that reason, new cybersecurity regulation as well as medical device regulation need to enforce a more thorough process to protect sensitive data.

With more patient health data being available for research and decision making, the field of personalized medicine will grow as well. The examples presented indeed indicate clearly that thanks to connecting information about the individual patient across different data sources, high quality and efficient personalized care can be achieved. Clinicians can use such collected evidence to deliver individualized therapy and increase the likelihood of successful treatment, as well as limiting the wasting of scarce resources. To fully utilize the potential of Big Data in personalized healthcare, health policymakers should, however, redefine the definition of its value, especially in the field of medical devices and healthcare services [35].

For instance, new terms have appeared such as 'theranostics', a biomarker-based diagnostics, which is having a significant impact on the development of therapeutic and diagnostic agents [36]. The introduction of such innovative approaches utilizing multiple data sources requires pricing and reimbursement decision making focused more closely on the patient's perspective. Therefore, a new type of outcome-based healthcare framework needs to be promoted that allows the use of Big Data even if it is generated through multiple sources including innovative diagnostics and therapeutics.

7.1. Five-year view

The growing amount of data will continue to provide a multitude of valuable insights that will transform the way we observe reality [37]. Big Data and AI will be key drivers of healthcare transformation. The multi sourced data will redefine the search for the optimal allocation of healthcare resources. Both personalized medicine and patient centric healthcare organization will become a new norm.

Big Data will inform decision-making processes on national, local, and individual levels. Patients and clinicians will use data analytics to optimize treatment pathways. Payers will use data analytics in several ways. For example, decision makers might utilize Big Data to develop conditional coverage schemes for very expensive and complicated health technologies. That would mean that reimbursement would be granted if an AI algorithm predicts success with a given treatment for that individual patient. More advanced payers may utilize data analytics even further and develop AI-based pricing schemes. For instance, if AI algorithms predict a maximal effect for a certain health technology, a maximal reimbursement may be guaranteed; whereas, if the model only predicts 50% of the maximal effect for an individual patient, only 50% of the maximum price will be reimbursed. Based on subsequent data for those patients, these algorithms may be adapted as well as the percentages of the maximum price reimbursed.

In order for such algorithms to work efficiently, future data analytics will elevate personalized medicine to a more sophisticated level taking into account environmental and lifestyle variability [38]. It will focus on individual needs in disease prevention and treatment by providing tailored made clinical care [39].

New healthcare models will be patient centric with the patient being the center of the decision making processes. To achieve that, electronic medical records will be populated with exposome information. Exposome has been already defined well by Gary Miller [40]. This captures the totality of additional human environmental and non-genetic exposures from birth and onwards [41]. Three main groups of additional information play a major role in that respect: (a) the general external environment, including the urban environment, education, climate factors, social capital, and stress; (b) the specific external environment with specific contaminants, radiation, infections, and lifestyle factors (e.g. tobacco, alcohol), diet, and physical activity; and (c) the internal environment, including internal biological factors such as metabolic factors, hormones, gut microflora, inflammation, and oxidative stress. There are already examples of how exposome impacts the management of modern immune-mediated diseases (IMDs) that cause huge economic, societal, and medical challenges. Machine learning will be further utilized as it is the case in the ongoing research projects (i.e. HEDIMED) to develop multi-exposure data analysis methods that helps to gain a better understanding of the effect of different exposures on health outcomes.

Enforced by changes introduced with GDPR, a patient centric healthcare model will shift the data ownership from healthcare providers to individuals as well. With the convergence of IoT, Big Data and Machine Learning with Telemedicine, E-health, M-Health the patient will become a point of access to the healthcare system. Instead of requests submitted to ethical committees, researchers will be asking individuals to grant the access to their health data. According to the recent estimate by Gartner, the current split between 80% vs 20% of data being processed in centralized computing facilities and smart connected objects linked to mobile phones ('edge computing') respectively will be change significantly by 2025 [42]. It is estimated that already today around 70% of the US and UK population is involved in the self health monitoring [43].

Therefore the future challenge will be related not only to the data ownership but also methods supporting unstructured data handling. There are numerous tools and techniques available to perform analytics on Big Data. The interoperability and data modeling will be the cornerstones of this new era that has been branded Healthcare 4.0. In this new era, all nations, providers, payers, and patient associations will be working intensively to structure data, streamline terminologies, reengineer, and simplify healthcare processes. The European Commission is operating already in that domain by enabling new funding opportunities for AI, supercomputing, and interoperability [44]. A new information model is currently being implemented to allow a massive information exchange of structured data: the European Electronic Healthcare Record exchange format (EHRxF) [45]. It is growing need to align operating standards with the current information exchange protocols for Big Bata, IoT, device connectivity, 5 G, and machine learning. HL7 FHIR is paving the way for this new information exchange era and IHE international is already enabling new integration profiles that include this innovation, already tested during connectivity marathons, also known as Connectathons® [46].

As the result of these efforts, the standardization of healthcare procedures and the enforcement of clinical treatment pathways will become a new norm across various jurisdictions [47]. Both the US and the EU have already issued new policy documents that will enforce the robustness in reuse of medical information by establishing proper data structuring and information exchange models [48]. The EU Commission also went one step further by proposing 27 IHE integration profiles for procurement purposes across all EU member states [49].

Development, validation, and standardization of outcome-based healthcare models are going to be instrumental in the further adaptation of data analytics in healthcare. Different interest groups, such as the patients, clinicians, technology producers, and HTAs, are urged to unite these initiatives.

The processing capacity of computing facilities does not seem to be a hurdle any longer. Healthcare has already embraced health IT and Big Data to enable digital transformation. It will be based on a huge network of connected people, devices, and software systems. Studies state that Healthcare 4.0 will include more than 24 billion connected Internet of medical devices (IoMT) by the end of 2020 that will create an ocean of medical information whereby Big Data and other technologies will revolutionize healthcare [50]. These immense volumes of information are coming in from multiple sources that are connected within this expanding IoMT network. Healthcare 4.0 is a trend transforming healthcare processes and business models, thereby enabling healthcare providers to expand precision medicine, transform care delivery, and improve the patient experience. In the last decade, our ability to analyze larger sets of data in a reasonable period of time has enabled us to move forward in the healthcare sector and provide adequate tools that assist the clinicians in their daily work. As a result of predictive analytics, we now have the ability to include new data sets that enable personalized medicine. Through the creation of 'digital twins' we can add more information into data models to predict the future [51]. In addition to classic clinical information (i.e., laboratory results, medical imaging), we can now process genomics, behavioral, or social determinants to enable personalized medicine schemes. Digital twins are near real-time digital replicas of a human organ or individual. Clinicians will soon be able to provide personalized treatment for each patient based on the results of such predictive analytics tool. When creating a digital twin for a hospital, capacities, staffing, operational strategies, and care models can be analyzed to determine what actions to take [52]. Current best practices in predictive analytics are the ELIXIR intra-governmental organization that includes 220 research organizations from 22 countries [53]. ELIXIR brings together life science resources from all around Europe. These resources include databases, software tools, training materials, cloud storage, and supercomputers that enable the use of complex data sets in healthcare such as genomics, metabolomics, metagenomics, proteomics, and more.

Other new cutting-edge technologies developed thanks to Big Data, such as robotics, 3D printing, brain-computer interfaces, brain-to-brain interfaces, noninvasive electronic diagnosis, and patient–physician interaction networks deliver new dimensions to patient centric value-based healthcare. As the result, a change of paradigm from the treatment-based system to a prevention based healthcare model will be anticipated with better outcomes delivered within limited healthcare resources.

Despite technological advancements, there are numerous social and cultural values defining local context in which healthcare systems operate. The legal regulations are established as a safeguards to protect national interests and local principles. As a result different pathways both the development and utilization of big data can be anticipated. The very recent example of coronavirus outbreak proves that. For example Chinese government collects routinely data on citizens' migration and even launched a mobile app called 'Close Contact Detector' to allow people to verify whether they were in close contact with someone infected and whether they are at a increased risk. In addition to that, the Chinese authorirites are using more than 200 milion survialnce cameras to to spot people potentially infected. 'AI temperature measurement system' uses thermal cameras in that respect [54]. In contrast to the Chiense experience, there is ongoing discussion in the EU whether automated facial recognition breaches GDPR, as the technology fails to meet the regulation's requirement for consent [55,56]. Such example indicate that the legal regulations established on the grounds of social and cultural principles across jurisdictions may lead to differences how Big Data will impact the future development of value-based pricing, the transparency of decision making, and healthcare waste reduction.

In sum, we acknowledge that the role of Big Data in the transformation of healthcare in an era of limited resources will continue to grow. Still, however, the current implementation is mainly ad hoc and generally on a local level [52]. New frameworks where the patient will be genuinely empowered to handle his/her health and data will be needed. There is still underutilization of the multiple data sources because of the current unstructured approach. This is especially true for complex, noisy longitudinal, and voluminous data. Therefore, clinicians should work with data analysts to establish a clinically meaningful reporting format. Access to Big Data is not only important at the national level but also at the international level. The collaboration in the field of diagnostics and treatment can increase the knowledge volume. Such a possibility will certainly enrich the research potential, especially in areas where knowledge is limited. Some authors suggest that value and variability truly define Big Data [57]. This provides hope in anticipation of the future. There is no problem with innovation in the field of data analytics in healthcare but there is a problem with its adaptation.

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