Big data and artificial intelligence for health system sustainability: The case of Veneto Region

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Ricevuto il 31 maggio 2020
Accettato il 19 febbraio 2021

Abstract

This paper investigates the digitalization challenges facing the Italian healthcare system. The aim of the paper is to support healthcare organizations as they take advantage of the potential of big data and artificial intelligence (AI) to promote sustainable healthcare systems.
Both the development of innovative processes in the management of health care activities and the introduction of healthcare forecasting systems are valuable resources for clinical and care activities and enable a more efficient use of inputs in essential-level care delivery. By examining an innovative project developed by the Regional Social Health Agency (ARSS) of Veneto, this study analyses the impact of big data and AI on the sustainability of a healthcare system. In order to answer the research question, we used a case study methodology. We conducted semi-structured interviews with key members of the organizational group involved in the case. The results show that the implementation of AI algorithms based on big data in healthcare both improves the interpretation and processing of data, and reduces the time frame necessary for clinical processes, having a positive effect on sustainability.

Keywords: Big Data, Artificial Intelligence, Sustainability, Healthcare System, Digitalization, Health Planning.

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Management Control (ISSN 2239-0391, ISSNe 2239-4397), 2021, 1 – Special Issue
Doi: 10.3280/MACO2021-001-S1003

1. Introduction

The process of digitalization has increased the speed at which new technologies are transforming most sectors, including the healthcare sector (Winter & Davidson, 2019). The volume of healthcare systems data is increasing exponentially, encouraging the use of technologies such as artificial intelligence (AI) (Flores et al., 2013). Healthcare markets in Europe and the U.S. have been valued at hundreds of millions of euros and are expected to grow to over EUR 7 billion in Europe and EUR 14 billion in the United States by 2027 (PRN, 2017).

Big data can be generated by many sources and can be defined in various ways (Kruse et al., 2016; Wang & Krishnan, 2014). In healthcare, the term "big data" refers to the automated collection and storage of electronic data (Eichler et al., 2016) and includes links between databases that improve the performance of the healthcare system (Bates et al., 2014; Miotto et al., 2017). While big data promise to deliver significantly improved health outcomes at significantly lower costs, it has yet to be implemented fully (Adibuzzaman et al., 2017).

The increasing availability of big data in healthcare allows for the implementation of predictive models based on AI systems that can revolutionize the way in which clinical and managerial activities are carried out, and the attendant timeframes. Thus, AI can free health professionals from routine activities and save lives by detecting risky conditions in a timely and efficient manner (Accenture, 2016; Jiang et al., 2017). In the same way, predictive models can be powerful management tools to support health planning and programming. In summary, in the field of healthcare, as in other areas, AI has the potential to introduce new sources of growth, changing the way in which people work and the effectiveness of such work (Holmes et al., 2014; Perkmann & Schildt, 2015).

In addition, AI analysis of population data allows for personalized and relevant individual care. Health care tailored to an individual has a greater impact on behavioral change, which is key to improving health and reducing the risk of illness (Cupertino et al., 2018; Mariani et al., 2016). To provide this level of care effectively, health resources must be optimized to enhance patient experience, improve the health of the population, reduce per capita costs and enhance health care provider satisfaction (Bodenheimer & Sinsky, 2014).

European health systems face important challenges related to the sustainability of healthcare, from both an economic point of view and in relation to the quality of health services provided in terms of the continuous improvement of effectiveness, safety, and clinical and organizational appropriateness (OECD, 2016). The ability of EU Member States to continue to provide high-quality care to all depends on healthcare systems becoming more resilient and sustainable. Thus, it is necessary to strengthen the promotion of health and the prevention of illness, to invest in primary care systems, to move healthcare out of the hospital and into more affordable outpatient care, and to develop practices of integrated care.

In order truly to be sustainable, the health system should use a definition of sustainability that is not exclusively linked to environmental issues. Indeed, the sustainability of the health system must be understood in terms of economic, environmental and social sustainability to satisfy the different interests and needs of all stakeholders (Buffoli et al., 2013; Osorio-González et al., 2020).

Economic sustainability considers managerial, technological and clinical aspects. Hospital management, which takes into consideration environmental issues and social responsibility, represents a key area in which healthcare systems can reduce their contribution to environmental problems affecting the world today (Infante et al., 2013). Healthcare companies should consider the impact of their activities, in the form of natural resource use, on the environment by integrating environmental management into work routines (Osorio-González et al., 2020). Social sustainability refers to a process that leads to stable development with an equal and appropriate distribution of income, thus creating a reduction in differences between different social levels of society and improving the living conditions of the population (Machado et al., 2015).

In this context, AI plays an essential role in helping to develop a vision of an inclusive society that is capable of simultaneously safeguarding individuals, communities and the environment (MISE, 2020). Similarly, the use of big data can have a positive impact on sustainable development, by enabling the production of intelligent information that can save resources in the process of generating statistics (Jiang et al., 2016). Indeed, big data enables the transformation of imperfect, unstructured and complex data into processable information, resulting in timely decisions in response to particular situations affecting people’s well-being (ECLAC, 2014; Priyanka & Nagarathna, 2014).

Today, most studies focus on the potential benefits of implementing AI and using big data (Ahir et al., 2020; Frederick et al., 2019), while few researchers explain how this technology can support the sustainability of the healthcare system (ECLAC, 2014). This study aims to fill this gap by analyzing the case of the innovative project launched by the ARSS of Veneto, Italy (Regione del Veneto, 2017), that focuses on the impact big data and AI have on the sustainability of a healthcare system. The Veneto Region is one of the Italian regions with an interest in new technologies. In 2020, 21.6% of the total Italian information and communications technology (ICT) expenditure (EUR 6.8 billion) was supported mainly by the Emilia Romagna and Veneto regions. We chose the Veneto Region because it can be considered a best practice example. Indeed, the Veneto Region is a promoter of the use of machine learning algorithms to automatically classify digital clinical documents and extract the most significant clinical information from unstructured ones (ARSS del Veneto, 2009). Additionally, the Veneto Region, in collaboration with the SAS Institute, has launched a feasibility analysis to verify the actual ability of predictive models based on AI algorithms to predict the trend in healthcare demand (ARSS del Veneto, 2009).

The goal of our research is to answer the following research question:

RQ: In which ways do AI and big data support the sustainability of healthcare systems?

The results of this study will help healthcare organizations harness the full potential of big data and AI for the promotion of sustainable healthcare systems.

From this perspective, the development of innovative processes in the management of health care activities and the introduction of healthcare forecasting systems are valuable for supporting clinical and care activities and can enable a more efficient use of information in the delivery of essential care. Digital transformation in healthcare can be a springboard for the development of new business models, as it fosters changes in work processes, improvements in productivity, reductions in cost and improvement of the patient experience.

The paper is structured as follows: Section 2 reviews the literature, and Section 3 outlines the research methodology, which is based on a single case study. Section 4 provides the results, delving into the impact of new technologies on the sustainability of a healthcare system; and section 5 presents a discussion and our conclusion.

2. Literature background

2.1. Artificial intelligence in healthcare systems

The digital revolution can be defined as the transition from mechanical technology to digital devices. It began in the 1950s and continues to this day, accelerated by computing (Baryannis et al., 2019).

AI refers to activities aimed at building intelligent systems. The particular techniques used in AI activities range from the use of traditional symbolic AI, based on representations of mathematical or knowledge-based problems, to sub-symbolic AI, including fuzzy systems and evolutionary calculus, to statistical AI involving machine learning (Baryannis et al., 2019).

In the past, the main limitations of AI have been the scarcity of sufficient data for learning algorithms and the inability of AI systems to manage data in its natural form, requiring the transformation of raw data into meaningful characteristics. Deep learning is a subset of machine learning that relies on huge amounts of raw data to improve model performance. Today, data digitization has enabled deep learning algorithms to leverage big databases to improve the performance of a learning model and extend the sophistication and scope of AI applications (Jordan & Mitchell, 2015; Kamel Boulos et al., 2019). Deep learning is already used in a wide range of areas, including healthcare (Siwicki, 2017; Winter & Davidson, 2019).

By using AI to analyze population data, it is possible to identify unknown patterns that can predict adverse health events for individuals. The information is personalized and most relevant to the individual because it is based on their specific data. Personal health information tailored to an individual has a greater impact on behavioral change, which is key to improving health and reducing health-related risk (Cupertino et al., 2018; Mariani et al., 2016). The requirement to operate such a platform, however, is access to patient and individual data in vastly greater quantities than was previously possible.

For personalized, predictive and preventive healthcare to become a reality, analytical results from a large population with multiple data sources (Flores et al., 2013) will need to be collected and combined. The growing stockpiles of digitized health data available from research and commercial agreements are central to the process of deep learning innovation in the healthcare sector (Murdoch & Detsky, 2013).

Thus, the drivers of the digital revolution in healthcare include changes in the behavior of patients as they become more proactive in their own care (Fox & Duggan, 2013), healthcare costs as they relate to a need to use resources efficiently, and evolving regulations that incentivize hospital managers to make significant use of health information technology (HHS, 2013). It is necessary to involve the digital revolution in healthcare to optimize health resources, seeking to procure high quality care at the lowest possible cost. For AI to produce the desired effects, a large amount of health data from individual patients is needed. The number of personal health information databases is growing quickly (California Healthcare Foundation, 2014; Eichler et al., 2016) and, over time, will be used to create deep learning algorithms in the growing range of AI healthcare applications (Abidi & Abidi, 2019; Bates et al., 2014; Cohen et al., 2014; Miotto et al., 2017).

2.2. Big data in healthcare systems

The information science involves the accumulation, storage, processing and application of big data. Clinical computing is a field within information science that improves human health by implementing information technology and knowledge management to prevent disease, provide more efficient treatments, and make transferal research effective (Abidi & Abidi, 2019; Health Care Information and Management System Society, 2017). In essence, clinical computing is the science of healthcare information, and it serves as a bridge between big data and its various applications.

Big data refers to large sets of information that exist in organized, unstructured or mixed formats (Kruse et al., 2016; Wang & Krishnan, 2014). It also reflects information accumulated in real time, the source of the information, and the maintenance of the quality of the information (Mariani et al., 2016; Petrosino et al., 2018). These features of big data have been called the paradigm of the five Vs: volume, velocity, variety, veracity and value (Adibuzzaman et al., 2017; Kruse et al., 2016; Mcafee & Brynjolfsson, 2012; Patgiri & Ahmed, 2017). It is difficult to accurately determine the amount of data generated annually across the healthcare sector due to the complexity of the information, the heterogeneous nature of the sources, and the variability of structured and unstructured formats in which such data exist (LeSueur, 2017).

Data analysis is used to better understand the health challenges of populations based on geography, age, race, gender and socio-economic situation (Cooper et al., 2001); and it is also useful for public health surveillance (Brownstein et al., 2009). Big data promise to deliver significantly improved health outcomes at lower costs, but healthcare systems have not yet fully implemented the use of big data (Adibuzzaman et al., 2017). Big data have the potential to change the way public healthcare is managed and improved. However, population data have disadvantages in terms of their collection (Winter & Davidson, 2019) and data ethics (Wänn, 2019) that limit usability.

Firstly, the collection of health data is rarely carried out in real time. This means that all conclusions using that data are based on past events, and thus are too old to be useful for individual intervention. Secondly, in response to growing concerns about data ethics and negative social consequences, interdisciplinary scholars have begun to develop field experiments that detect discrimination resulting from AI and big data analysis (Sandvig et al., 2014). Consequently, it is worth pointing out that deep learning methods can be used to detect involuntary or intentional social effects from deep learning.

In addition, the implementation of big data in improving the quality of healthcare is not without limits and setbacks. Big data is prone to errors, and its application can lead to misleading conclusions if the dataset is full of artefacts caused by flaws in equipment, technique, observation or data collection (Spacey, 2017).

Data security also remains a challenge, because all software applications have vulnerabilities, and user behavior can increase security breaches in a healthcare system. For instance, hospital staff may share or use computer access passwords that are easy to crack. The infrastructure, experience and tools needed to use big data effectively are not widely available and are difficult to use, making large-scale collaboration impossible (HIMSS, 2017; Hsieh et al., 2013; Mcluckie, 2017; Mohr et al., 2013).

In terms of data management specifically (Khatri & Brown, 2010), new forms of inter-organizational data governance are being developed to exploit big data in healthcare, such as advanced analytics, distributed research networks (Holmes et al., 2014) and the creation of collaborative data in genetic research and clinical trials (Perkmann & Schildt, 2015; Susha et al., 2017). Effective health data governance remains a primary focus for organizations facing countless challenges (Rosenbaum, 2010). First, digitization and dissemination of healthcare data often result in a lack of data standardization and interoperability that currently present barriers to the sharing and use of clinical data, including use in advanced analytics and AI applications. Second, regulations on the disclosure of health data have limited information flow and increased the cost of accessing health data (Lane & Schur, 2010). Finally, health monitoring devices and applications have resulted in patient-generated health data resources developing outside clinical settings and without regulatory oversight (Deering, 2013).

Despite existing challenges, there are unrelenting social and regulatory pressures to make health data more available for research and innovation (Siwicki, 2017), in order to achieve the digital transformations in health services envisaged by these developments.

Given the sensitivity of personal health data and existing legal and regulatory protections, approaches to clinical data governance are more mature than in many other socioeconomic areas (Rosenbaum, 2010). However, existing data governance structures are unlikely to be sufficient to control the combined momentum of AI, deep learning and clinical data aggregation, or to help channel developments in socially beneficial and fair directions.

Health organizations are generally resistant to change, so changes in health care activities must be encouraged by first changing consumer behavior (Edwards & Saltman, 2017). Digital platforms will attract many third-party providers seeking to offer health advice and additional analytics.

This ecosystem of suppliers will be able to offer consumers high-quality monitoring and advice at low cost, and without the cumbersome qualities of the current healthcare system with its long wait times and low consumer satisfaction (Wänn, 2019).

2.3. The link between AI, big data and sustainability

In healthcare systems, sustainability must be defined as economic, environmental and social sustainability to satisfy various interests and needs of all stakeholders (Buffoli et al., 2013; Osorio-González et al., 2020). Economic sustainability includes criteria related to managerial, technological and clinical aspects. The health system is a significant part of a country's economy. However, a well-functioning health system requires a robust financing mechanism; a trained and adequately paid workforce; reliable information on which to base decisions and policies; and effective structures and logistics to provide quality services (World Health Organization, 2011). Consequently, healthcare sustainability is increasingly considered from an economic point of view, especially in countries like Italy, which have traditionally achieved almost uncontrolled levels of healthcare expenditure.

AI plays an essential role in building a path towards realizing a vision of an inclusive society that protects individuals, communities and the environment. There is no doubt that the demand for technology solutions focused on sustainable development is set to increase significantly over the coming years. This means asking how the use of technology such as AI can reduce poverty and hunger, remove social and gender inequality, provide quality, equitable and inclusive education, ensure access to water and energy resources, protect the environment, ensure growth and decent work for all, and strengthen institutions and social justice (Miotto et al., 2017; MISE, 2020).

With regard to environmental sustainability, hospital management is considered a key area in which healthcare systems can reduce their contribution to environmental problems (Infante et al., 2013). Healthcare companies should consider the impact of their activities on the environment, in the form of natural resource use, by integrating environmental management into work routines (Buffoli et al., 2013). The healthcare system, and hospitals in particular, utilizes more or less three times the energy consumption of a residential building of equal size, not counting water consumption (D'Alessandro et al., 2016; Ji & Qu, 2019). In addition, these structures continually produce high quantities of air emissions, together with solid and liquid waste that can also be hazardous or toxic (Cantlupe, 2010). AI can be used effectively to improve the production, management and distribution of natural resources. New ecosystems will be based on faster and smarter paradigms, and depend more on data and technology. The management of large volumes of data means that actions can be coordinated and monitored along value chains, enabling efficient control of products and externalities (ECLAC, 2014; Wang & Krishnan, 2014). New sustainable, digitized and autonomous technologies are emerging, and simultaneously creating new models of growth and natural resource management (Sharon, 2016). AI algorithms can optimize existing models by rapidly delivering increased efficiency, for example through predictive maintenance, so machines can learn to monitor and maintain themselves, negating the need for costly emergency repairs or the introduction of automated customer service robots or energy trading (MISE, 2020; Vinuesa et al., 2020).

Finally, social sustainability refers to a process that leads to stable development with a fair and appropriate distribution of income, thus creating a reduction in the differences between the different social levels of society and improving the living conditions of the population (Machado et al., 2015). Hospitals also have a significant social impact, hosting a variety of different individuals from different cultures and with different histories and professional backgrounds (Capolongo et al., 2015). From the perspective of the United Nations' Sustainable Development Goals, one of the aspects of greatest importance is the use of AI tools to solve or at least mitigate some "ethical" issues in the service of citizens. In this sense, AI technologies can be of great support to the achievement of the Sustainable Development Goals, and in particular the third and tenth goals (good health and well-being for people; reducing inequalities) (Vinuesa et al., 2020). AI entails, on the one hand, a risk related to the well-known ethical problems; but on the other hand it represents an opportunity for the creation and development of products that respond to social challenges, and that include, from the earliest stages of their development, a reflection on and attention to respect to ethical, responsible and sustainable approaches. AI can provide the conditions to create an interconnected environment in which users and stakeholders are able to find a range of data and tools useful to strengthen integration policies and effectively consolidate results in the medium and long term (MISE, 2020; Truby, 2020). It is precisely in this sense that big data could be adopted to obtain real-time information on people's well-being, and to direct the interventions of institutions in the field of social sustainability as well (Bates et al., 2014; ECLAC, 2014).

3. Research methodology

In order to answer the research question, we used the methodology of a case study (Yin, 2014). This is particularly useful for studying phenomena that are under-explored (Eisenhardt, 1989), such as new digital technologies and their relationship to the sustainability of a healthcare system. This methodology also has the advantage of guaranteeing a high level of understanding of the complex reality examined (Berg, 2004).

The research was conducted using a single case study which was selected because it is highly representative of the application of AI and big data in the health sector.

In relation to the research objective, and taking into account the current immature phase of the development of new technologies, the analysis of the case study is exploratory, as it provides preliminary explanations with respect to the research question; and further empirical investigations are thus required.

3.1. Research context

The Regional Social Health Agency (ARSS) of Veneto, Italy, launched a feasibility analysis to verify the effective capacity of quantitative models in predicting the trends in healthcare demands.

The project was carried out with the participation and contribution of various actors. Four health authorities were involved: Hospital of Padua, Local Health Units (ULSS) 16 of Padua, ULSS 10 of San Donà and ULSS 6 of Vicenza. Each group provided information on its history of drug dispersal for a period of 36 months. Following a statistical analysis of the historical series provided, consumption forecasts were generated.

The second actor was the SAS Institute, which provided the forecasting tool implemented during the trial (SAS® Forecast Server). The forecast server is a computational engineer that generates large-scale forecasts using AI tools in a primarily automatic mode. Using a wide range of statistical algorithms, the tool simultaneously analyzes hundreds of thousands of time series, building a statistical model for each one that best suits the characteristics of each series.

The third party involved was the ARSS of Veneto, which was both the promoter and coordinator of the project. The ARSS interfaced with hospitals to procure the datasets, and with computer scientists for aspects relating to the hardware running the SAS forecast. In addition, the ARSS managed communication with the SAS Institute in relation to the IT application and the search for solutions and methodological support for the implementation of the forecasting tool.

3.2. Data collection

Semi-structured interviews were conducted with the Director of the Operational Unit "Management Control", the Manager of the Operational Unit "Regional Epidemiological Service and Registers," and finally with a technical assistant who is in charge of data management and software. Open responses were used to understand the relationship between AI, big data and the sustainability of the healthcare system. Each interview, lasting about 60 minutes, was conducted electronically. In addition, we analyzed documents that included i) regional economic and finance documents, such as the Planning Document of the Veneto Region containing the strategic guidelines used by the administration in the period 2018-2020; ii) the papers of the Regional Social Health Agency of Veneto; and iii) articles published in national newspapers relating to the AI infrastructure tests conducted by the Veneto Region. The use of multiple data sources made it possible to triangulate the information and increase the reliability of the results that emerged from the interviews.

3.3. Data analysis

The data analysis is developed using the theoretical framework developed by Abidi et al. (2019). We examine the nature of health data using the big data criterion. We also explain how artificial intelligence-based data analysis methods work and discuss the contribution of new technologies to improve health system management, health outcomes, knowledge discovery and health innovation.

All interview data and findings were discussed between the authors to ensure investigative triangulation and with the interviewees to achieve validation of the findings (Yin, 2014), following the open coding method (Strauss & Corbin, 2014). This method consists of clustering the collected interview data into conceptual sub-categories related to the main topics explored. We used an interpretive approach based on narrative analysis and qualitative data collection (Crane, 1999). This analytical approach is considered appropriate for the study of new technologies (Aborisade, 2013) and the transformation of health big data (Iyamu & Mgudlwa, 2018).

4. Results

The Regional Social Health Agency (ARSS) of Veneto started the project in 2009. Initially, the project concerned all the resources of the four healthcare companies. Subsequently, given the amount of data that had to be processed and analyzed, the Agency decided to limit the field to pharmacies and diagnostics, and then limited the scope again to focus exclusively on medication. This choice was made because drugs can be presented as objects, which can guarantee results almost on a par with diagnostics, while it can reasonably be assumed that using predictions relating to medical devices would provide less satisfactory results than using those predictions related to drugs, given the intrinsic coding limits and the lower correlation with DRG and diagnosis. For all other possible input types, it is not currently possible to hypothesize merit assessment in the absence of a preliminary analysis of the characteristics of the historical series.

We conducted a feasibility analysis by feeding the SAS® Forecast Server application the consumption data of the four healthcare companies spanning a period of three years. In addition to consumption data, the time series of some production variables were provided that can potentially be used to explain the need for healthcare resources.

In the first phase, we uploaded the withdrawal data for the four companies. Then we defined the rules for structuring the data and the statistical analyses to be carried out. We activated two data uploads at two different time points, both beginning with the insertion of data regarding health activities in terms of DRG and the diagnosis attributed by the hospital staff.

The first upload was related to the period from March 2006 to February 2009, producing a forecast for March 2009 to February 2010. The methodology adopted by the SAS statisticians involved analyzing the historical series present in each cost center. This involved the analysis of over 140,000 series, of which only about 4% were complete. The forecasts generated with this data set were deemed unsatisfactory, so we took a different approach. The second upload related to the period from July 2006 to June 2009, producing a forecast for July 2009 to June 2010. In this case, a different method of analysis was used, passing to historical series by company article. The number of series was reduced to around 7,000, of which only 26% were complete. The greater degree of completeness made the second approach more effective for statistical analysis and provided greater predictive capabilities.

Finally, the technicians of SAS and ARSS carried out a statistical evaluation to assess the quality of the forecasts made by the system.

The lack of structuring in the process to define the needs and consequent risks, together with new needs deriving from the creation of the healthcare "Area Vasta," (Big Area) prompted the Regional Social Health Agency of Veneto to start a project with the goal of creating a forecasting system for the needs of healthcare sources.

According to an interviewee, effective management of the forecasting process requires a collaborative and cross-functional approach. The health system, in particular, contains complex interactions that must be managed through dialogue between company functions. For example, the purchasing function needs to correctly manage the lead time of the procurement process and to increase the number of alternative and equally effective products; the clinical functions (such as Health Technology Assessment (HTA) and medical management) need to express complex technical evaluations that often lead to the specialization of the products to be supplied; pharmacy structures express specifications for product management; the logistics manager must govern the flows by balancing the needs of users with the efficiency of the warehouses; and the controller must ensure compliance with the economic and budget constraints.

It was therefore essential to involve professionals – supervisors, pharmacists, controllers and IT technicians – working within the various company functions. In fact, this innovative project investigated not only the possible positive effects of the introduction of a planning tool, in terms of accuracy of the forecasts generated, but it also investigated the organizational impacts and possible modifications needed for the use of the resources involved in the planning process.

In the early 1990s, following the corporatization of the health service in Italy, managerial tools and logics were introduced as part of the planning process (Legislative Decree 502 of 1992). This process consisted of the disclosure of budget estimates, a scheme that still constitutes the main programming document. Over the years, the various structures that make up planned health care activities have operated independently of one another. Even today, at a national level, the programming done by the pharmaceutical department is not connected to the programming involving hospital beds, which is different from that done in the personnel office. Each section is an independent silo in which programming is primarily bound to subordinate basic logics. Over the years, the autonomous companies that traditionally made up the health system have been replaced by regionally based companies with common objectives and management areas. Budgets are defined at a regional level, and individual silos must deal with these budgets. Thus, the process is essentially a compatibility check more than a programming activity. This is the current method of planning used in the national healthcare system of Italy. The Veneto Region is trying to unify this system, reducing the independence of the different silos and encouraging the creation of a structure able to receive directives from above and organize services within a compliant perspective. Nowadays, technologies based on AI algorithms and capable of handling large amounts of data support the planning and programming process, making it more efficient and effective. This will make it possible to provide regional and national management with much more relevant and, above all, up-to-date planning information.

These objectives were achieved with the project launched by ARSS Veneto in collaboration with Ca Foscari University. From a qualitative point of view, the pharmacists' information and the software's predictions had the same negligible error; however, the most interesting finding was that the pharmacists were wrong as often as the machines were. From an efficiency point of view, the reduction of the time required to process the data was an important result: the pharmacists worked for months to produce a hypothesis of requirements that they would then reproduce years later, while the machine took one evening, with the ability to repeat the same analysis daily.

According to the interviewee, AI made it possible to obtain more significant margins of utility. With the implementation of AI systems, and more generally, of new technologies, daily programming that is updated continuously is possible, rather than the simple rituals used now. The costs will be reduced because the processes will be continuous. Thus, while the cost of implementing technology is decidedly high, the benefit derived from the reduction in time is significant. The interviewee pointed to a current lack of major qualitative changes, since these are management processes, and, thus, quality is still in the hands of the ultimate decision maker.

The project was the result of an attempt to unify all the complex operational units of *Azienda Zero,*[1] and to look for transversal needs in order to integrate the various silos, leading to an important response for all units. The project considered the possibility of using AI tools and technologies in managerial processes, specifically those processes that refer to the area of programming. The goal was the automation of procedures, including administrative ones: the Veneto Region wants to see that new technologies replace human involvement in routine operations, which may require continuous learning methods. In this sense, AI can be useful, although there are bound to be professional challenges. The adoption of new technologies includes the challenge of retraining the professionals themselves so that they can manage the machines. According to the interviewee, "*it is not the machine that must govern man, but the man who must govern the machines. Whoever manages to climb the skills pyramid will still be able to be competitive in the workplace, otherwise it is also a professional risk.*"

It emerged from the interview that there are still entire processes in the fields of management and administration that operate without any level of automation. Consequently, it is expected that the implementation of AI will require enormous efforts regarding knowledge, skills and the use of technology.

In the administrative area, databases present the main problem. For technological solutions to produce the desired effects, it is necessary to have large databases, and these databases require the availability of skills and tools capable of managing them.

Presently, the databases needed are those containing health services and personal data. These are databases that are different from each other in relation to health services, but common in relation to personal data. The civil registry is a single database where the status of the subject can be updated (any change of residence, travel from one region to another, deaths, ticket exemptions, etc.). The same sources are also used in the Adjusted Clinical

[1] Azienda Zero pursues the development of the regional health service based on participatory methods that are based on paths marked by maximum transparency and responsible sharing, in compliance with the principle of efficiency, effectiveness, rationality and economy in the use of resources, in order to continue to ensure equal access to services, while safeguarding territorial specificities.

Group software, a system for stratifying the population by disease and risk classes related to comorbidity. The stratification by risk categories is useful to estimate the health needs of the population and to make the allocation of resources more efficient. This not only improves health planning and programming, but also ensures more effective care. The ACG software also aims at providing healthcare professionals and programmers with predictive information about the types of patients who will get sick or whose condition will get worse. This counts as preventive medicine that allows professionals to anticipate problems and address them before they arise.

A further consequence of the implementation of new technological solutions concerns the ways in which the public sector collaborates with the private sector. For this, the Veneto Region has set up the Arsenàl.IT Consortium, involving health companies aimed at developing interoperability systems. The consortium is a hybrid public-private organization that allows IT technology to be dynamic even in the acquisition of skills, which is impossible in the public healthcare system.

According to the interviewees, in such a dynamic context it is necessary to identify forms of public–private partnerships that allow the timely use of all that technology can offer.

5. Discussion and conclusion

Digitalization has accelerated the pace at which new technologies are transforming most sectors, including healthcare (Winter & Davidson, 2019). The volume of data in European healthcare systems is growing exponentially, favoring the implementation of predictive models and AI systems capable of revolutionizing the ways in which clinical and managerial activities are carried out, and the time it takes.

European healthcare systems are facing important challenges related to the sustainability of healthcare, both from an economic and financial point of view, and in terms of the quality of health services provided, when these are understood as the continuous improvement of efficacy, safety, and clinical and organisational appropriateness.

In this study we considered how the Italian National Healthcare system is dealing with the challenges of digitalisation with the intent to support healthcare organisations to harness the full potential of big data and predictive models based on AI algorithms, in order to promote a sustainable healthcare system.

Our analysis focused on a single case study, selected because it is illustrative of the phenomenon under investigation. The project initiated by the ARSS of the Veneto Region clearly involved the possibility of using AI tools and technologies to plan and program healthcare resources.

According to existing literature, the economic sustainability of the healthcare system is relevant, especially in countries like Italy, where healthcare spending has traditionally reached almost uncontrolled levels. The implementation of AI algorithms, combined with the use of big data, can positively affect economic sustainability by significantly reducing the costs and time required for data processing (MISE, 2020). In this sense, the interviews revealed that the implementation of AI systems allows for daily programming with continuously updated data, which can reduce costs. Although there will still be significant costs associated with the installation of the technology, the benefit for human resources is undeniable.

Thus, AI can be useful, despite the professional challenges of retraining professionals and teaching them to manage machines effectively. The interviews indicated that the main problems are related to the databases, infrastructures and skills currently available. Although there are obstacles, the implementation of AI can significantly enhance the planning and programming system of a National Healthcare System, improving accessibility to care and consequently eliminating disparities resulting from socio-cultural differences. AI algorithms can contribute to ensuring good health and well-being for people as well as reducing social inequalities (Vinuesa et al., 2020). AI represents a significant opportunity for the creation and development of products that meet societal challenges and include reflection and attention to ethical, responsible and sustainable approaches. AI can foster the creation of an interconnected environment where users and stakeholders can find a set of data and tools to strengthen inclusion policies and effectively consolidate results in the medium and long term (Truby, 2020).

In conclusion, we believe that the implementation of machine learning systems and the use of big data will make it possible to program and plan the needs of healthcare input in real time, significantly reducing the cost and time necessary for programming activities. Real-time planning and programming, which can be achieved by implementing AI algorithms and exploiting big data, will improve economic sustainability (in terms of reducing time and costs), environmental sustainability (in terms of reducing the use of natural resources), and social sustainability (in terms of accessibility to care, regardless of socio-cultural differences).

To this end, our article provides a basis for assessing the impact of new technologies on the sustainability of the national healthcare system, both from a financial point of view and in terms of effectiveness of healthcare outcomes and of organizational and clinical appropriateness. Good planning will make it possible to better predict, prepare for and fulfil future health care demands. The delivery of high-quality care will depend on the ability of healthcare systems to become more resilient and sustainable in economic, social and environmental terms.

Although further empirical evidence is required, this study reveals interesting insights into the ways in which the Italian Healthcare System is preparing for the challenges brought about by new technology.

This study has theoretical and practical implications. First, it contributes to the existing literature by improving understanding of the importance of using AI and big data to improve health system planning and programming. Second, it offers health system practitioners not only elements to appreciate the effects of implementing AI and using big data, but also preliminary ideas regarding ways in which sustainable development strategies will be supported by the use of AI and big data algorithms.

The main limitations of the paper are due to the fact that the project is not yet fully mature and therefore the overall long-term advantages and disadvantages of implementing new technologies at all levels of the sector could not be appreciated.

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