The role of Information and Communication Technologies in Healthcare: Taxonomies, Perspectives, and Challenges

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Abstract

Progress in *Information and Communication Technologies* (ICTs) is shaping more and more the healthcare domain. ICTs adoption provides new opportunities, as well as discloses novel and unforeseen application scenarios. As a result, the overall health sector is potentially benefited, as the quality of medical services is expected to be enhanced and healthcare costs are reduced, in spite of the increasing demand due to the aging population.
Notwithstanding the above, the scientific literature appears to be still quite scattered and fragmented, also due to the interaction of scientific communities with different background, skills, and approaches. A number of specific terms have become of widespread use (e.g., regarding ICTs-based healthcare paradigms as well as at health-related data formats), but without commonly-agreed definitions. While scientific surveys and reviews have also been proposed, none of them aims at providing a holistic view of how today ICTs are able to support healthcare. This is the more and more an issue, as the *integrated* application of most if not all the main ICTs pillars is the most agreed upon trend, according to the *Industry 4.0* paradigm about ongoing and future industrial revolution.
In this paper we aim at shedding light on how ICTs and healthcare are related, identifying the most popular ICTs-based healthcare paradigms, together with the main ICTs backing them. Studying more than 300 papers, we survey outcomes of literature analyses and results from research activities carried out in this field. We characterize the main ICTs-based healthcare paradigms stemmed out in recent years fostered by the evolution of ICTs. Dissecting the scientific literature, we also identify the technological pillars underpinning the novel applications fueled by these technological advancements. Guided by the scientific literature, we review a number of application scenarios gaining momentum thanks to the beneficial impact of ICTs. As the evolution of ICTs enables to gather huge and invaluable data from numerous and highly varied sources in easier ways, here we also focus on the shapes that this healthcare-related data may take. This survey provides an up-to-date picture of the novel healthcare applications enabled by the ICTs advancements, with a focus on their specific hottest research challenges. It helps the interested readership (from both technological and medical fields) not to lose orientation in the complex landscapes possibly generated when advanced ICTs are adopted in application scenarios dictated by the critical healthcare domain.

Keywords: Healthcare, ICTs, e-health, m-health, pervasive health, WBAN, Cloud Computing, Internet of Things, Fog, Big Data, Genomics, health monitoring, privacy, security, interoperability.

1. Introduction

Healthcare represents one of the most important social and economic challenges that every country faces: today healthcare administrators, clinicians, researchers, and other field practitioners are encountering increasing pressure generated by the growing expectations from both the public and the private sector. While the rising cost of medical care has a major impact on the quality of people's life (even higher in the case of chronic diseases), constant population growth and aging influence health-

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care demands and dictate the need for new and more advanced scientific solutions [62, 213].
From the beginning of the 1990s, the Information and Communication Technologies (ICTs)—driven by the rise and the success of the Internet—played a major role in improving the access, the efficiency, the quality, and therefore the effectiveness of any process related to the healthcare. The concept of *e-health*, that can be broadly defined as the application of ICTs to healthcare, has therefore come in common use. Recent years have witnessed great public interest in the e-health sector, as well as unprecedented levels of investment in terms of both research effort and funding [108].
While the e-health is enjoying the uninterrupted development of new information technologies solutions [229], the specific characterization of the term is subjected to progressive changes and specifications, according to the widespread range of opportunities and issues raised by the evolution of the ICTs. In today's world, where all the involved entities are connected to each other by some communication means, *anywhere-and-anytime connectivity* is becoming a solid reality for a growing number of scenarios. In addition, availability of computing resources at lower cost and higher integration scale benefited the healthcare practices (*ubiquitous and pervasive computing*). The unprecedented spread of wireless and mobile technologies also among the poorest gives a sense of the raise of this technology as well as of its potentialities. Technology advancements and mass market demand led also to the spread of low-cost sensing devices suitable for a number of goals (e.g., low-power, miniaturized, non-invasive and lightweight wireless sensors able to monitor either the human body functions or the surrounding environment and generating large amounts of data) [285]. These circumstances also allowed new hardware infrastructures (e.g., huge-scale datacenters leveraging virtualization technologies) to be deployed all over the globe and accessible to the general public, thus implementing scale economies. Above all, two paradigms, i.e. the *Internet of Things* (IoT), based on intelligent and self configuring nodes interconnected in a dynamic and global network infrastructure, and *cloud computing*, that makes available virtually unlimited storage and processing power on demand, enable a plethora of applications and services in a number of different scenarios [36]. The aforementioned technologies, together with the rising availability and quality of medical software applications—often coming in the shape of *mobile apps*—drove to the rapid integration of mobile devices into clinical practice [291].
While these *ICTs paradigms* are assuming several specific connotations in the healthcare domain, on top of them a number of specific *ICTs-based healthcare paradigms* have emerged in the last years. These ICTs-based paradigms are redesigning modern healthcare with promising technological, economic, and social prospects. These advancements in ICTs are going to mitigate a number of long-lasting issues pertaining to the health sector (e.g., backing people suffering from obesity or chronic diseases as well as aging population) [44] where they support the growth of digitized data produced by the medical and clinical community providing advanced techniques for the management of the computing and storage resources as well as enabling advanced practices (e.g., large-scale data analysis) [229, 330].
The massive adoption of advanced ICTs technologies is dramatically changing the health-sector landscape, generating *new opportunities* as well as introducing new applications and rejuvenating or reinventing the classical ones. Cooperation among practitioners is improved, as teams of health professionals can effectively work together, coordinating their activities, sharing their knowledge about the patients, and ensuring to provide the best coordinated care. Thanks to technology advances, first-hand health monitoring and medical care is facilitated [44]. More in general, the adoption of the latest technologies helps governments provide value-added services to citizens and discloses a number of opportunities. For instance, chronic diseases can be now better faced leveraging prevention through monitoring [27]. Patient-centric services can be provided and basic needs of citizens can be addressed quickly. Resulting health systems enable citizens to have more control on their own well-being, by accessing personalised and qualified health information and accessing appropriate medical care even from their homes, also thanks to remote health monitoring [252, 184] or ambient-assisted living solutions [195, 236]. Treatment methods can be improved, health professionals can manage their activity more efficiently, and the quality of hospitals and medical services can be also conveniently monitored [16]. With the concept of *P4 Medicine* [259], that is *predictive*, *preventive*, *personalized* and *participatory*, the idea of medicine itself is radically changing. Based on a comprehensive understanding of an individual's own biology, P4 Medicine is

going to tailor treatments to the individual characteristics of the patient, in contrast to the current approach of clustering patients into treatment groups according to their phenotype. This approach is predicted to significantly cut down global health budgets, both by reducing the need for hospitalization as well as other associated costly procedures and by minimizing the unnecessary and inappropriate use of drugs [206, 59].
In this scenario, the implementation of proper artificial intelligence (AI) solutions to handle and analyze the huge amount of health-related data available today—that often assumes the characteristics of *big data* [234]—is crucial.
Besides the discussed opportunities, the adoption of these technologies also extends a number of *ICTs issues* into the healthcare domain, even exacerbating some of them because of the health-sector critical constraints. Security concerns, data privacy, system design and performance, critical service availability, data and systems heterogeneity are the most recurring issues to be addressed.

1.1. Methodology, contribution, and scope

Guided by the relevant best practices [165] and leveraging both *Google Scholar* and *IEEE Explore* search engines, we have selected almost 600 scientific publications dealing with the adoption of ICTs in the healthcare domain. Then, based on scientific relevance (quantified through citations count, number of downloads, publication venue, as well as quality and novelty of the study as emerging from the abstract, the introduction, and the conclusion sections) we have filtered out more than 300 scientific papers. Analyzing the full text of these papers—mainly published between 2011 and 2016—we are able to provide an up-to-date characterization of the scientific literature, identifying the main *ICTs-based healthcare paradigms* originated in the last few years, as well as the *ICTs paradigms* and the *ICTs technology pillars* that underpin them. Figure 1 briefly summarizes them.

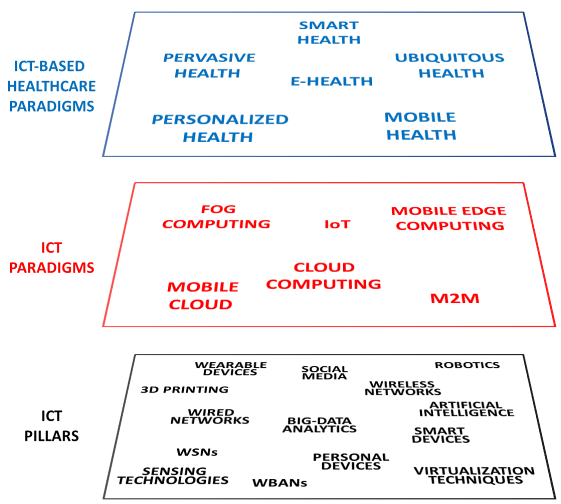

Figure 1: ICTs pillars and ICTs paradigms underpinning the identified ICTs-based healthcare paradigms.

The remainder of the paper is organized as follows. Based on the surveyed literature, we provide in Section 2 the description for the main ICTs-based healthcare paradigms (*e-health*, *mobile health*, *personalized health*, *smart health*, *ubiquitous health*, and *pervasive health*), also highlighting inconsistencies stemming out from the definitions we found. Section 3 reports the evolution of the different formats proposed for managing health-related data. In Section 4 we analyze the main ICTs pillars (such as *communication and networking technologies*, *smart devices*, *wireless sensor and body area networks*, *big-data analytics*, *robotics*, *social networking*, *3D printing*, and *artificial intelligence*) and the enabling ICTs paradigms (such as *machine-to-machine communications*, *IoT*, *cloud*, *fog* and *mobile edge computing*), together with their characteristics, also discussing the main drivers to their implementation. Section 5 surveys the main applications born from the adoption of the identified pillars in the health domain. In Section 6, the main issues and challenges deriving from the adoption of ICTs in the health sector are discussed. Finally, Section 7 draws the concluding remarks.
According to the implemented structure, the content of the paper, and the variety of the topics addressed, this paper (i) sheds light on how specific ICTs-related terminology is adopted by the scientific community working in the healthcare field; (ii) contributes to identify all the main ICTs that play a critical role in the delivery of healthcare services, together with the issues they raise and the opportunities they give birth to when migrated to the health domain.
Therefore, the intended readership for this paper is composed of both (i) field experts who have familiarity with a subset of the addressed topics, as the survey helps understand how these topics relate with each other and with the other main subjects possibly encountered when dealing with ICTs applied to healthcare; (ii) laymen about ICTs (e.g., practitioners from the medical field), as this sur-

vey provides a broad technical picture of how the adoption of an up-to-date set of cutting-edge information technologies proves to be fruitful when adopted to the critical health domain.

1.2. Related Work

In the scientific literature a large number of surveys can be found dealing with the adoption of one of the identified ICTs pillars in the health domain. Although the presence of these studies is a marker of the interest the scientific community has in the topics this paper deals with, to the best of our knowledge none of these studies provides a holistic view of how ICTs support healthcare. This is the more and more an issue, as the massive adoption of ICTs in healthcare is but a case of a generic trend towards full digitalization of human activities, along what is gaining consensus as the fourth industrial revolution (dubbed *Industry 4.0*, see [280] for its application to health). Such paradigm shift sees the integrated adoption of most—eventually, all—the ICTs main pillars in the production and service chains. Therefore a partial view of ICTs applications to the health domain falls short of providing the necessary holistic knowledge. This motivated our contribution and sets this paper apart from the related work.

In the following we report the more relevant surveys of ICTs applications to health, grouped according to the ICTs pillar or paradigm mainly addressed.

Cloud. The huge adoption of cloud technologies in the health domain has been surveyed in several works. Ermakova et al. [90] aim at identifying the state of research related to the adoption of cloud computing in the health domain. Pino and Di Salvo [229] propose a survey concerning the current models of health that are switching to solutions based on cloud computing. Calabrese and Cannataro [42] review the main cloud-based healthcare and biomedicine applications. Abbas and Khan [2] aim to encompass the state-of-art privacy-preserving approaches employed in the e-health clouds.

IoT. Several surveys discuss the adoption of IoT in healthcare. Laplante and Laplante [176] present a structured approach for describing IoT for healthcare, by defining general classes of system types. Islam et al. [136] survey the advances in IoT-based healthcare technologies and review state-of-the-art network architectures, platforms, and applications, as well as industrial trends in IoT-based healthcare solutions. Yeole and Kalbande [320] describe various applications that IoT enables in the area of healthcare. Darshan and Anandakumar [74] address the use of IoT in healthcare, discussing the challenges of IoT in healthcare systems and review various works carried out on this research area.

Wu et al. [311] provide a vision of the machine-to-machine (M2M) paradigm and analyze the future directions and network architectures evolution to enable the mass deployment of M2M services, also considering the healthcare use case.

Wireless communications. Different applications of wireless communications (**Wireless Sensor Networks, Wireless Body Area Networks**) have been surveyed in relation to healthcare. Ko et al. [167] report how wireless sensor networks (WSN) for healthcare have emerged in the last years and survey most representative applications in healthcare domain, also describing the related challenges. Alemdar and Ersoy [9] provide a number of state-of-art examples about the adoption of WSN in healthcare, together with design considerations like unobtrusiveness, scalability, energy efficiency, and security.

Latré et al. [177] and Chen et al. [56] present an overview of the concept of Wireless Body Area Networks (WBAN) and a discussion of WBAN communication types and their related issues. Cao et al. [44] survey pioneer WBAN research projects and enabling technologies. Filipe et al. [100] compare technologies and protocols published in the most recent researches, seeking WBAN issues for medical monitoring purposes to select the most useful solutions for this area of networking.

Big Data. The new features and promises, as well as the new challenges and risks, brought by Big Data applied to healthcare are the subject of several surveys. Ramesh et al. [235] summarize the role of big-data analysis in healthcare and various shortcomings of traditional machine learning algorithms. Sun and Reddy [270] analyze key problems and trends in healthcare analytics research. Archenaa and Anita [16] give an insight of how additional value can be uncovered from the data generated by healthcare and government. Zou et al. [330] propose a survey on the MapReduce-based applications that can be employed in the next-generation sequencing and other biological domains.

Table 1: Surveys on adopting ICTs pillars and paradigms in the healthcare domain (in chronological order) and related topics.

Authors	Year	Cloud	IoT	WBAN	Big Data	WSN	M2M	Networking Technologies	3D Printing	Robotics	Fog and Mobile Cloud	Social Networks	Artificial Intelligence
Taylor and Stoianovici [276]	2003									✓			
Taylor [275]	2006									✓			
Haux et al. [121]	2009			✓		✓							
Cao et al. [44]	2009			✓									
Ko et al. [167]	2010					✓							
Alemdar and Ersoy [9]	2010					✓							
Latré et al. [177]	2011			✓									
Chen et al. [56]	2011			✓									
Wu et al. [311]	2011		✓				✓						
Yoo et al. [321]	2012												✓
Griffiths et al. [115]	2012											✓	
Ermakova et al. [90]	2013	✓											
Pino and Di Salvo [229]	2013	✓											
Sun and Reddy [270]	2013				✓								
Zou et al. [330]	2013				✓								
Abbas and Khan [2]	2014	✓											
Malik et al. [190]	2015								✓				
Calabrese and Cannataro [42]	2015	✓											
Laplante and Laplante [176]	2015		✓										
Islam et al. [136]	2015		✓										
Darshan and Anandakumar [74]	2015		✓										
Filipe et al. [100]	2015			✓									
Archenaa and Anita [16]	2015				✓								
Burgner-Kahrs et al. [41]	2015									✓			
Yeole and Kalbande [320]	2016		✓										
Ramesh et al. [235]	2016				✓								✓
Kassahun et al. [157]	2016									✓			✓
Ciuti et al. [64]	2016									✓			
This paper	2017	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Yoo et al. [321] provide a summary of various data mining algorithms together with their respective advantages and drawbacks, and introduce how data mining technologies (in each area of classification, clustering, and association) have been used for a multitude of purposes, including research in the biomedical and healthcare fields. Tomar and Agarwal [282] survey various data mining techniques in health domain, also highlighting applications, challenges, and future issues.

Robotics. The last decade has seen progressive adoption of robot-assisted processes in medicine: the state-of-art and current research is surveyed in the following works. Taylor and Stoianovici [276] provide a broad overview of medical robot systems used in surgery. They introduce basic concepts of computer-integrated surgery and discusses some of the major design issues particular to medical robots. Taylor [275] discusses some research areas related to healthcare robotics such as modeling and analysis of anatomy and task environments or interface technology between data and physical world.
Burgner-Kahrs et al. [41] describe the state of the art in robot manipulators and systems intended for application to interventional medicine. Reviewing current research on Wireless Capsule Endoscopy applied to gastrointestinal tract diagnostics and therapy, Ciuti et al. [64] provide an overview of the frontiers of in-vivo microrobotics. The review provided by Kassahun et al. [157] is focused on ML techniques directly applied to surgery, surgical robotics, surgical training and assessment.

Social Networks. The new possibilities opened by Online Social Networks, as well as ne new risks, are considered in the work of Griffiths et al. [115], that analyze how self-organizing, adaptive networks could become central to future health care delivery. They consider whether social networks composed of patients and their social circles can compete with, or complement, professional networks in assembling health-related information of value for improving healthcare.

3D Printing. Malik et al. [190] review the current applications of 3D printing in modern surgical practice, and report that the three main areas in which this technology is adopted are printing (i) anatomic models, (ii) surgical instruments, and (iii) implants and prostheses.

Other. Surveys that do not focus mainly on a specific ICTs pillar are reported in the following.
The aim of critical review proposed by Honka et al. [128] is to identify the barriers which are holding back the growth of the market related to the adoption of ICTs in the health domain.
Focusing on ICTs solutions addressing HIV/AIDS and malaria, the report proposed by Bordé et al. [34] reviews examples from different regions of the world where ICTs is leveraged for decreasing child mortality and improving maternal health.
With goals similar to ours, in 2009 Haux et al. [121] proposed a literature review surveying the information and communication technologies enabling healthcare, but only focusing on one of the ICTs-based paradigms we discuss in this paper (i.e. pervasive healthcare—see Section 2) and emphasizing the role of WBAN and sensor networks. Moreover, due to the evolution of the cutting-edge technologies, it lacks a discussion of novel technology solutions that have gained popularity in recent years, such as cloud computing, IoT, big-data analytics, etc.
Table 1 summarizes the surveys available in the literature and compares the topics discussed by them to those discussed in this paper. As shown in the table, differently from the available literature this paper attempts to provide a picture of the overall healthcare-oriented ICTs scenario. Therefore our survey is intended to be much more complete and aims at providing a holistic picture of how ICTs support healthcare. In addition, our study is up to date and discusses a broader range of pillars we have been able to identify today according to the ICTs evolution. As a result, when compared to the state of the art, it presents—for the first time in the literature—a unified view and scientific survey of the main ICTs pillars applied to the health domain; it also permits to relate the different pillars and discuss the more recent applications of ICTs to health, generated by the mixture of these ICTs pillars.

2. ICTs-based Healthcare Paradigms

In recent years, ICTs improvements played a key role in the progress of available healthcare solutions. Rapid advances in information technology and telecommunications—and more specifically in wireless and mobile communications offering anywhere-and-anytime connectivity—are leading to the emergence of a new type of information infrastructure that has the potential of supporting an array of advanced services for healthcare.

Riding the wave of the technological progress, a number of healthcare-related paradigms has been introduced. Often, a new terminology is adopted without providing a formal definition for the adopted neologisms. For this reason, in this section we survey the most recurrent ones. Although it is hard to provide a formal and sharp taxonomy, we aim at focusing on their peculiarities, providing for each of them the characterization derived from the literature.

2.1. E-health

E-health (also spelled ehealth) is a widely accepted neologism since the 1990s (it dates back to at least 1999 [77]) when a number of *e-terms* (e.g., e-mail, e-commerce, etc.) began to proliferate, together with the success of the Internet. The introduction of e-health represented the promise of ICTs to improve health and the healthcare system.

E-health is a general term, and despite the lack of an agreed-upon clear or precise definition, it encompasses the use of ICTs in the support of healthcare and health-related activities. However, usage of the term varies, to the extent that Oh et al. [211] in their study found up to 51 unique definitions for e-health. Indeed, while some authors adopted the term to describe the combined use of electronic communication and information technology in the health sector [199], others used it in the narrower sense of healthcare practice using the Internet [303].

E-health can be subdivided into several domains, such as: telemedicine and telecare, clinical information systems and clinical information networks, big-data large-scale integration and analysis of heterogeneous data sources [67].

Being the older among the proposed paradigms, according to some definitions it may also include newly introduced health-related paradigms, such as *mobile health* or *personalized health* [67].

2.2. Mobile health

Mobile health (also known as m-health) aims at delivering healthcare services regardless of any mobility constraints, i.e. overcoming geographical, temporal, and organizational barriers [256]. It supports direct access to health services regardless of time and place and allows to reduce high costs of existing national health services. Indeed, it empowers patients and families to self-care, being suitable to help address both chronic and lifestyle-related disease, by providing the scalability needed to cope with the increasing number of elderly and chronic-disease patients requiring constant monitoring [19].

Laxminarayan and Istepanian [178] defined mobile health for the first time in the year 2000 as *unwired e-med*. Over time, the concept has evolved according to technological changes in communication protocols and infrastructures that moved from GSM, GPRS, satellite, and wireless LAN to 4G and—more recently—5G networks. Indeed, when the concept was introduced, 2G and 3G technologies were envisioned as the main enablers, and examples of potential services included mobile ECG transmissions, video images and teleradiology, wireless ambulance services, and other integrated mobile telemedical monitoring systems [178]. 4G health represents the long-term evolution of m-health, defined as the evolution of m-health towards targeted personalized medical systems with adaptable functionalities and compatibility with the (future) 4G networks [139].

According to common practices implemented today, where mobile technologies such as *smartphones* and *mobile apps* are emerging as powerful tools for health-information transfer, these technologies are commonly considered pillars for the m-health paradigm, being able to support medical and public-health practice, health-information delivery, patient screening, monitoring of physiological signs, direct care, and patient education [67, 310, 181].

With the advent of 5G and the implementation of an ecosystem that includes heterogeneous networks and integrates 4G, Wi-Fi, millimeter wave, and other wireless access technologies, m-health paradigm will be subjected to further evolution, leveraging the advanced capabilities and opportunities of 5G (e.g., reduced latency, richer media services, etc.) [307].

2.3. Personalized health

Personalized health is *user-centric* i.e. it targets to take patient-specific decisions, rather than stratifying patients into typical treatment groups [136, 126, 293, 67, 213]. Sometimes it is referred to as *adaptive health* [108].

According to the available technological solutions, personalized health may resort to *user segmentation* that consists in subdividing the population (ideally per service or group of related services), into more or less homogeneous, mutually exclusive subsets of users and can be implemented leveraging personal

Table 2: Summary of ICTs-based healthcare paradigms and their constituting aspects.
Legend:
•: element *usually* found in literature definitions;
○: element *possibly* found in literature definitions.

ICT-based healthcare paradigms \ Characteristics	ICT	Internet	(Broadband) mobile connectivity	Personal smart devices and mobile apps	Ubiquitous computing and ambient intelligence	Pervasive monitoring	User centrality	Context awareness	Service deinstitutionalization
E-Health	•	○							
Mobile Health	•	•	•	○	○	○			
Personalized Health	•	•		○		•	•		
Smart Health	•	•	○	○	○	○		•	
Ubiquitous Health	•	•		○		•			
Pervasive Health	•	•		○		○			○

mobile devices and taking into account thematic preferences and device profile [108]. These subdivisions are possibly based on demographic, socio-economic, or individual physical and psychological characteristics.

A key element is the possibility of gathering multiple data from patients and the environment, as data analysis facilitates health and social care decision making and delivery. Data sources could be wearable or implantable micro- and nano-technologies with sensors or therapy delivery devices (e.g., fall detectors, implantable insulin pumps, defibrillator vests, etc.) [67]. Often, *personalized health monitoring* is required [300, 59, 149, 57] to support personalized healthcare/medical systems [284, 80] or personalized health guidance solutions [128, 326].

The concept of personalization and user centrality is further emphasized when applied to *P4 Medicine* [259, 206, 129, 127, 138], where the main data source considered is the genetic information of each individual. A comprehensive understanding of an individual's own biology (*personalized omics*) is expected to address both health and disease and to impact on predisposition, screening, diagnosis, prognosis, pharmacogenomics, and surveillance [59].

2.4. Smart health

Multiple definitions for SMART HEALTH can be derived from the literature, as this concept has been given multiple interpretations.
Sometimes, smart health is simply defined as medical and public health practice supported by smart mobile devices (i.e. smartphones) [181], therefore generating an overlap with the definition of mobile health (see section 2.2). A more comprehensive

definition—less focused on smartphones and embracing latest technologies at large—can be found in [22] where smart health is considered to be based on the use of technologies such as smart mobiles, smart cards, robots, sensors, and tele-health systems via Internet on pay-per-use basis for best medical practices [22].
Park and Kim [216] reported that smart health refers to the intelligent health management and medical service using information technology so that anyone can safely and freely use it anytime, anywhere.
According to Suzuki et al. [271], smart health integrates ideas from ubiquitous computing and ambient intelligence. Related processes generate large amounts of data being collected over a network under daily life and that is potentially valuable to monitor, predict, and improve patients' physical and mental conditions [271, 127].
Finally, Solanas et al. [262] consider smart health as the context-aware complement of mobile health within smart cities, i.e., it consists in the provision of health services by using the context-aware network as well as the sensing and actuation infrastructures of smart cities.
A number of works also refer to SMART E-HEALTH [7, 197, 150, 221]. According to Al Yami et al. [7], smart e-health is a term that generally refers to the use of ICTs in the healthcare field. Penmatsa and Reddy [221] report that there are three fundamental ways that smart e-health is affecting healthcare: patient treatment, disease management, and population health.

2.5. Ubiquitous health

UBIQUITOUS HEALTH supports enhanced quality of medical services and sustainable healthy life. It requires a dynamic network of interconnected systems that offers health services independent of time and location [244].
Ubiquitous health, initially helped provide prevention, diagnosis, treatment, and follow-up care without visiting doctor at anytime and anywhere. With the development of the medical technology, it has advanced to the pre-diagnosis and prevention of the diseases [202].
In more particulars, as reported by Lim et al. [185] ubiquitous healthcare aims at maintaining the subject's health level (wellbeing) by making many devices available throughout the physical environment. One of the key characteristics of ubiquitous healthcare is the adoption of (wireless) pervasive monitoring [244].

2.6. Pervasive health

Varshney [288] defined pervasive healthcare as *healthcare to anyone, anytime, and anywhere* by removing locational, time and other restraints while increasing both the coverage and the quality of healthcare.
According to Tan et al. [273], pervasive healthcare aims at delivering *deinstitutionalised* healthcare services to patients anytime and anywhere, as reducing institutionalization is a priority for most western countries, being a tool to face healthcare costs [171]. According to this provided definition, the concept of pervasiveness emphasizes more the social impact (healthcare available *to anyone*) rather than technological aspects. On the other hand, according to Sobrinho et al. [260] pervasive healthcare also consists in the use of pervasive computing paradigm concepts (e.g., IoT) in the provision of medical services at home.
Also, pervasive healthcare involves remote data collection through mobile devices and sensor network which the data is usually in large volume, varied formats, and high frequency [273].

2.7. Overall view

All the ICTs-based healthcare paradigms above are widely adopted by many academic institutions, professional bodies, and funding organizations. As an example of their widespread adoption, Figure 2 reports the number of scientific publications related to each of them published in the period of twenty years from 1996 to 2016.[1] The figure shows how the concept of both e-health and mobile health have been introduced and systematically adopted earlier by the scientific community. As a result, the total number of scientific publications citing them is dramatically higher. Another consequence is that these two concepts are provided with more consolidated definitions. Indeed, the precise meaning of all the other ICTs-based healthcare paradigms discussed in this section—as happens with most neologisms—often varies with the context in which each term is used. It is worth noting that some

[1] Statistics about the scientific literature are extracted adopting *Google Scholar*[113]. Although inferred results might be not 100% accurate, they provide useful insights about literature trends.

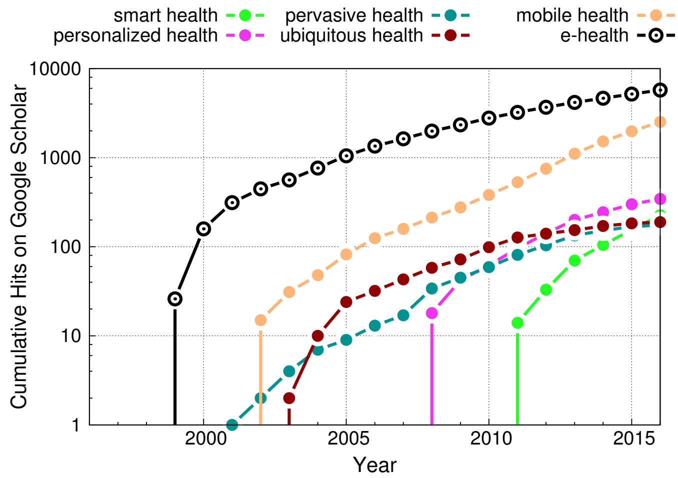

Figure 2: Popularity of ICTs-based healthcare paradigms measured as the number of publications related to each paradigm per year, from 1995 to 2016. Data source: *Google Scholar* (exact match in title). 2016 was the last year for which complete statistics were available at time of writing.

of them are sometimes even adopted interchangeably. For instance, Tan et al. [273] consider pervasive healthcare, ubiquitous healthcare, and mobile healthcare as synonyms. While we recognize—as for now—the impossibility of finding a universally acceptable, universally applicable formal definition for each of the terms identified, Table 2 summarizes the characterization of these terms stemming out from the scientific literature by focusing on their constituting aspects. The table confirms how all the cited paradigms depend on ICTs—above all from the Internet. On the other hand, some constituting elements (such as personal devices, ambient intelligence) resulted to be peculiarities of specific paradigms.

Being aware that the provided definitions may be subjected to changes (e.g., when the name of some of the paradigms such as e-health or m-health are adopted as umbrella terms), in Section 4 we will thoughtfully analyze the impact of ICTs advances on the healthcare sector discussing the ICTs pillars and paradigms supporting healthcare applications, rather than clinging to strict definitions.

3. Health-data formats

The systematic availability of health-related information is the core of the revolution ICTs is leading in the health sector. Health-related information may be gathered with a number of different goals in mind, and may come in a number of different formats. The overall lack of clarity by policy-makers, health professionals, and consultants fuels a general level of confusion; the fact that there is no standardized and accepted definition for each of the concepts commonly adopted, furthers this confusion. Not only a set of different formats is leveraged, indeed a huge number of terms has been proposed and adopted in the scientific literature over the time. Starting from this literature [152, 295, 257] and consulting the piece of documentation provided by international organizations involved in the health sector [310, 135], we gathered the most used terms adopted for identifying health-related data and formats and provide here their commonly accepted meanings, also analyzing their popularity in the scientific production. Figure 3 reports the popularity of terms discussed above. As a quantitative index for popularity, we leveraged the number of scientific publications according to Google Scholar. Note that only the top-ten terms (those with more than 20 occurrences) have been reported in the chart. As shown in the figure, the EMR (electronic medical record) and EHR (electronic health/healthcare record) are the two most popular terms with more than 15K occurrences each. Considering the others, more than 1K occurrences have been found only for EPR, PHR, and CPR.

The list of the discussed terms, together with the related acronyms is provided in the following. Con-

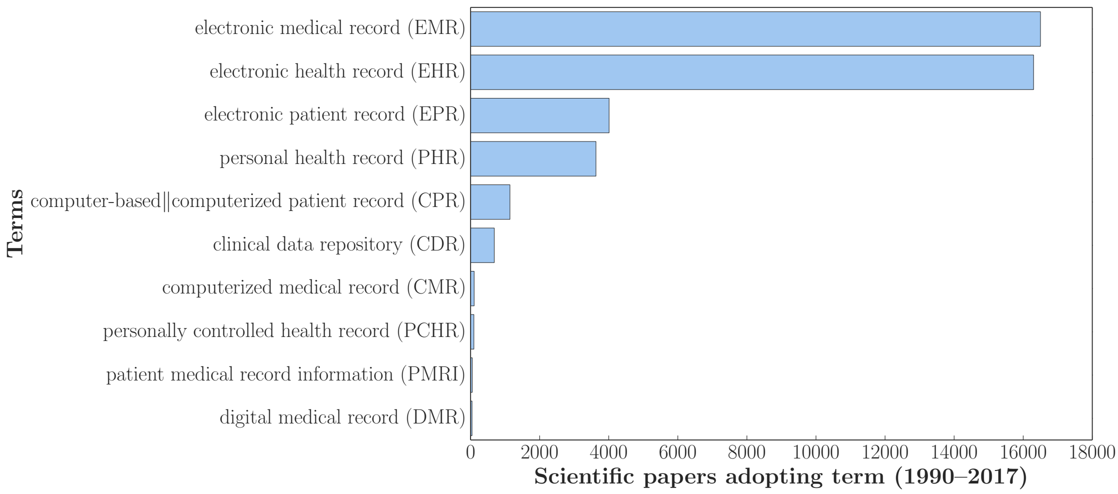

Figure 3: Health-data format terms popularity in the scientific literature (top-ten terms). Data source: *Google Scholar* (queries have been performed with strings exactly as reported for the labels).

sidering that some of the definitions are mutually related, we have decided to order the terms such to highlight the existing analogies and discrepancies.

An **electronic medical record (EMR)** is a real-time patient health record with access to evidence-based decision support tools that can be used to aid clinicians in decision-making. EHR is used by healthcare practitioners to document, monitor, and manage healthcare delivery *within a care delivery organization*.

In general terms, EMRs are clinician-focused in that they enhance or augment the workflow of clinicians or administrators. Furthermore, an EMR may contain clinical applications that can act on the data contained within its repository, for example, a clinical decision support system, a computerized provider order entry system, a controlled medical vocabulary, or a results-reporting system. The EMR can automate and streamline a clinician's workflow, ensuring that all clinical information is communicated, also preventing potentially dangerous delays in response and gaps in care. The EMR can also support the collection of data for uses other than clinical care, such as billing, quality management, outcome reporting, and public health disease surveillance and reporting [106, 257, 310].

According to the ISO standard definition [135], an **electronic health/healthcare record (EHR)** is a repository of information regarding the health status of a subject of care, in computer processable form. More specifically, an EHR is a *longitudinal* electronic record of patient health information generated by one or more encounters in any care delivery setting, and reporting episodes of care *across multiple care delivery organizations* within a community, region, or state [125, 106].

The EHR may consist in a subset of EMR from each from care-delivery organization, assumed to be summarized according to specific health-record standard specifications jointly developed by healthcare institutions [106]. The EHR can be established only if the EMR of the various care delivery organizations have evolved to a level that can create and support a robust exchange of information between stakeholders within a community or region [106]. Indeed, medical information systems today store clinical information about patients in a number of proprietary formats. To address the resulting interoperability problems, several EHR standards that structure the clinical content for the purpose of exchange are currently under development [87]. This notwithstanding, Iakovidis [134] emphasize how EHR is a powerful tool towards *continuity of care*, while confidentiality has to be ensured at all times.

EHR may include patient demographics, past medical history, medications, immunizations, laboratory data, radiology reports, vital signs, problems, and

progress notes [310, 257].
It is worth noting how according to Smolij and Dun [257] EHRs are created and maintained by healthcare institutions, while Garets and Davis [106] reported that they are owned by the patient.
The ISO standard also defines **electronic health record for integrated care (ICEHR)**, as a repository of information regarding the health status of a subject of care, in computer processable form, stored and transmitted securely and accessible by multiple authorized users. ICEHRs have a standardized or commonly-agreed logical information model that is independent of EHR systems and whose primary purpose is the support of continuing, efficient and quality integrated healthcare. It contains information which is retrospective, concurrent, and prospective [135].
A **personal health record (PHR)** is a layperson-comprehensible, lifelong tool for managing relevant health information, promoting health maintenance and assisting with chronic disease management. It is controlled and managed by the citizens (or their legal proxy). By definition, it is not a legal record unless so defined and is subjected to various legal limitations [310, 257].
A **personally controlled health record (PCHR)**, is a subset of PHRs [120], where the idea of strict patient control is central. With PCHR, individuals decide who can read, write, or modify components of their records. Access to the records is allowed only with patient consent, for identified, de-identified, and even aggregated data. This strict control model is intended to promote widespread adoption by inspiring confidence that the system will maintain privacy and confidentiality.
A **computer-based patient record (CPR)** is a lifetime patient record that includes all information from all specialties. According to the literature, it requires *full interoperability* (potentially internationally) and therefore it is unlikely to be achieved in foreseeable future [295, 257].
An **electronic patient record (EPR)** is similar to a CPR but does not necessarily contain a lifetime record. It only focuses on relevant information (e.g., may not include dental, behavioral, or alternative care) [96, 257].
A **patient-carried record (PCR)** defines the record with all information contained on a token or a card carried by patients. Most demonstrations and pilots projects leveraging this technology have been discontinued [295].
A **computerized medical record (CMR)** defines any document imaging-based system [96].
A **digital medical record (DMR)** defines a web-based patient record using pull messaging technology to achieve efficiency guaranteeing minimum of messages exchanges [96].
A clinical data repository (CDR)—also known as clinical data warehouse (CDW)—is a real-time database that consolidates data from a variety of clinical sources to present a unified view of a single patient. It is optimized to allow clinicians to retrieve data for a single patient rather than to identify a population of patients with common characteristics or to facilitate the management of a specific clinical department [189].
Finally, **patient medical record information (PMRI)** is the term adopted in the US Department of Health and Human Services. It consists in medical information on an individual patient generated by a healthcare professional as a direct result of interactions with the patient or with individuals who have personal knowledge of the patient. PMRI includes demographics and health history, details of present illness or injury and orders for care and treatment, observations and records of medication administration, test results, and referral information [123].
Besides those detailed above, a number of other terms appearing in the literature but having less than 20 occurrences also exist, such as integrated care record services (ICRS), population health record (PHR), electronic case record (ECR), and mobile health record (MHR) [295, 96].
Considering the supposed maintainer of the healthcare information, health records can be divided into two main groups: those maintained by healthcare institutions and those maintained by patients or consumers. Cases exist for which this aspect cannot be derived by the considered literature or is not relevant. Table 3 summarizes this aspect, cataloguing health-record formats by their maintainer.
It is evident how the overall scenario concerning the digitized data in the healthcare field appears very fragmented. This situation further complicates the analysis of this data, as also discussed in the following (see Section 4.9).

4. ICTs Pillars and Paradigms

According to the general trends observed—also outlined by the ICTs-based healthcare paradigms reviewed in Section 2—in this section we discuss the

Table 3: Health records with supposed maintainer.

	Maintainer		
	Healthcare Institution	**Patient or Consumer**	**Not relevant or Information not Available**
EMR	✓		
EHR	✓[257]	✓[106]	
ICEHR	✓		
CPR	✓		
EPR	✓		
P(opulation)**HR**	✓		
ECR	✓		
P(atient)**HR**		✓	
PCR		✓	
PCHR		✓	
CMR			✓
DMR			✓

main ICTs pillars and paradigms supporting the healthcare domain, identified by dissecting the scientific literature. The ICTs pillars we consider are summarized in Figure 4. As shown in the figure, we have decomposed the overall ICTs ecosystem in four subsets, according to the role played by each of the items. The subsets we have identified are: *communication*, *sensing*, *processing*, and *actuation*. It is worth noting how these subsets are not disjoint, as several pillars and paradigms can be placed in their intersections, as well as the concepts behind the items themselves have common elements in some cases. Figure 4 provides a useful guide to navigate throughout this section. In the following, we will discuss the ICTs pillars and paradigms in this order: (i) communication, (ii) sensing, (iii) processing, (iv) actuation.

4.1. Communications and Networking Technologies

Communication makes up an important part of the healthcare professionals' daily practices. Communication encompasses different forms of interaction and dissemination of health-related information, and takes place in contexts such as patient-professional relationships, and collaborative care. ICTs in the healthcare domain offers a useful means to support increased accessibility, exchange, and sharing of information and drives to a higher overall quality of healthcare services [11].

With rapid changes in both technology and healthcare institutions, online informatics is becoming more and more central. The **Internet infrastructure** is clearly the vehicle with the greatest potential to improve the dissemination of the information and to change the way healthcare is delivered [230]. The widespread availability of medical and scientific information on the Internet is having a profound impact on the relationship between patients and physicians (e.g., every year more and more patients turn to the Internet for medical advice). However, while having health-related information available electronically has numerous benefits, the delivery of this information to stakeholders has been less than ideal [223, 288].

The enhancement of **wireless communications**, stepping from the first implementations of local and wide Wi-Fi networks with enough performance for supporting both isochronous and bulk applications [156, 155], is a stepping stone in the improvement of the healthcare applications. Indeed, it is the main enabler of the m-health paradigm, also fulfilling the vision of pervasive healthcare by removing locational and time constraints, while increasing both healthcare coverage and quality [288].

Mobile broadband connectivity allows to reach new patients in remote areas, while improving productivity and convenience through data transmission, thus mitigating issues generated by limited coverage of healthcare services in rural and underserved areas that still exist worldwide [288]. In the context of an increasingly mobile society, the worldwide deployment of mobile and wireless net-

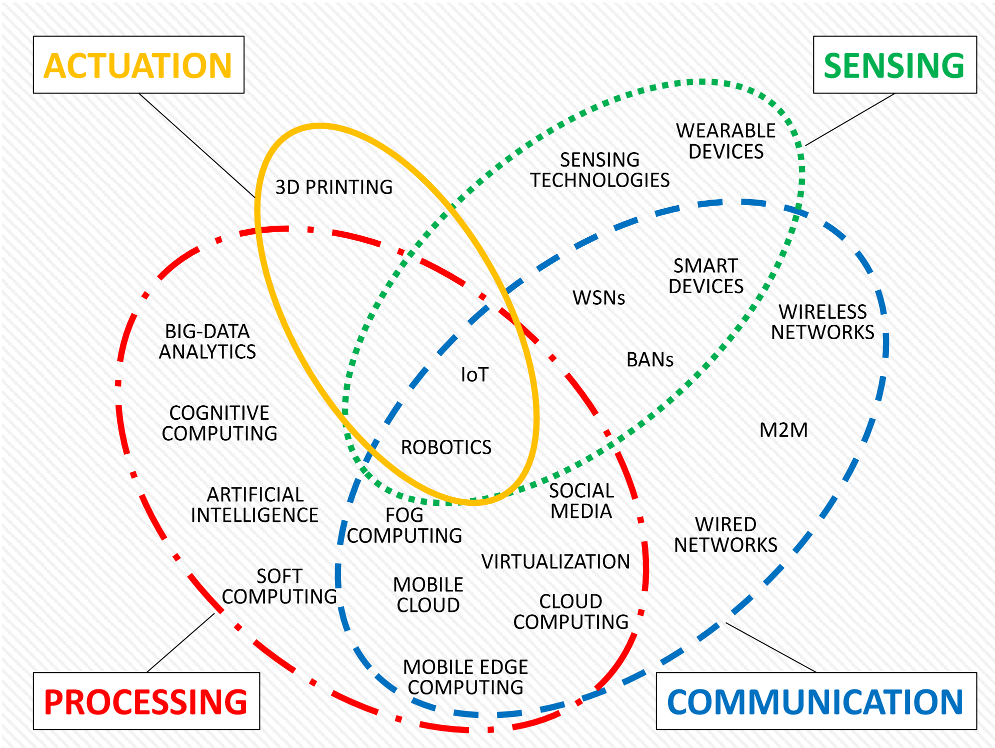

Figure 4: ICTs pillars and ICTs paradigms supporting the Healthcare domain.

work infrastructures can support many current and emerging healthcare applications [288].

As the mobile communications industry traveled a long way from 2G to 4G, now **5G networks** aims to change the world by connecting anything to anything [119, 80]. The system characteristics of 5G include high data rate, low latency, and high capacity, to support various challenging applications [58, 80]. However, drastic improvements need to be made in cellular network architectures to meet the existing demand. Related emerging technologies include massive multiple-input multiple-output technology, and device-to-device communication. Along with this, interference management, spectrum sharing with cognitive radio, ultra-dense networks, multi-radio access technology association, full-duplex radios, millimeter wave solutions, cloud technologies, and software defined networks are attracting the interest of the community [119]. 5G is paving the way for interconnecting the wireless world without barriers, enabling many challenging applications. This new technology is expected to support computing-intensive applications involving multi-dimensional massive data processing potentially assisted by (mobile) cloud [207, 85] (see Section 4.7 and Section 4.8). The scenario set up by the availability of these technologies will enable interactive and more personalized services [58].

Driven by healthcare-related scenarios, delay- and fault-tolerant network approaches have been also proposed and implemented to extend communication networks into challenged areas, e.g., for pervasive information gathering or in order to support facility to report medical-related data such as the level of the stock of medical drugs or the number of patients in a village to a healthcare authority located elsewhere [208, 301].

Many challenges, including considerable stress on healthcare-provider communication infrastructure and partial coverage of healthcare services in rural and under-served areas, still exist worldwide [288].

4.2. Machine-to-machine communication

The machine-to-machine communication (M2M) paradigm envisions billions to trillions of every-day objects and the surrounding environment connected and managed through a range of devices, communication networks, and (cloud-based) servers. To implement the M2M vision, availability of devices, ultra-scalable connectivity and infrastructures for centralized decision-making are required [311]. M2M communication for healthcare also relies on sensors to form a body area network (see Section 4.5).

In recent years, applying machines (e.g., sensors) to healthcare has attracted a tremendous amount of research interest. IEEE project 802 standardized under the umbrella of IEEE 802.15 wireless personal area networks (WPAN) and thus wireless body area networks (WBAN). Thus, today many healthcare systems adopt 802.15 WPAN, 802.11 WLAN, or Zigbee, leveraging their different transmission characteristics and data rates. Existing research focuses more at system integration of available devices to a central system, rather than at the design of the communication networks with a tremendous number of machines connected [54].

Healthcare is expected to rely on medical devices and systems (i.e., organizing machines) that are networked to ubiquitously match the need of patients in any circumstances [54]. Such healthcare systems enable intelligent hospitals, and allow to implement seamless control of medical and biological treatments and guided surgery and therapy. Leveraging reliable high-speed connectivity such as that guaranteed 4G/5G cellular networks, one of the primary services potentially enabled by M2M in healthcare is remote patient monitoring and care (see Section 5.1).

4.3. Smart and wearable personal devices

Smart personal devices (mainly in the form of smartphones) have penetrated significantly into society in a relatively short period of time. An entire spectrum of subscribers—covering differing ages, from school children up to senior and elder people—is reached through this technology [37]. This success has been built upon a long history of usage of communication devices from the beginning of the latter part of the last century. Today, mobile phones are at the vanguard of a cultural shift where users are encouraged to constantly seek out new information and make connections with increasingly dispersed media content [37].

Smart devices (smartphones, PDAs, or tablets), guaranteeing portability, constant internet connectivity, and enough computing power to run complex applications are key part of the e-health revolution that digitized the health sector. They have been an instrumental tool in the evolution of the healthcare-related paradigms, acting as the major catalyst for the transition of e-health to mobile health [223]. Indeed, they are considered as service mobile platforms for health information delivery, access, and communication [207].

The tremendous potential for mobile communication to transform healthcare and clinical intervention in the community is clear. Several previous studies have evaluated the use of mobile phones to support healthcare and public health interventions (e.g, in support of the collection and the integration of data for healthcare research as well as medical education, clinical practice, telemedicine and remote healthcare, information delivery in rural areas) [37]. With the advent of custom designed applications, the adoption of smartphones has rapidly expanded and a number of specialties are producing innovative specific applications (e.g., orthopaedic decision support applications, off-site radiology access, infectious disease tracking, storage of reference material) [223]. Also, smartphones have the potential to improve diagnostic skills and education of a surgeon [73]. More in general, pioneering advances and increasing applications of smartphone-based devices and applications in the exponentially growing field of m-health are expected in the next decade [289].

Smart devices can be equipped with and interfaced to a number of sensors that are commercially available, in easy and not expensive ways (see Section 4.4). Specialized devices which are either mobile equivalents of large cumbersome pieces of equipment or devices which interface with smartphones, enable physician to gather and transmit monitoring information [223]. These sensors can be attached on clothing or on the body or even implanted under the skin, and enable to implement a wide range of applications and services (see Section 4.5).

The availability of a continuum of devices—in the range from low-cost and low-power to compute-rich and high-performance—is one of the fundamental enablers of both the machine-to-machine (see Section 4.2) and Internet of Things visions (see Section 4.6), where large numbers of devices are expected to be embedded, requiring extremely low price points and low power consumption [311].

Advanced applications running on resource-limited mobile terminals are backed by specific paradigms and technologies. Mobile cloud computing (see Section 4.8) emerging in the context of 5G has the potential to overcome performance bottlenecks that potentially exist, thus enabling many resource-intensive services for mobile users with the support of mobile big data delivery and cloud-assisted computing [58, 37, 29].

4.4. Wireless Sensor Networks

As wireless sensor network technologies have become mature enough for improving the quality of life, they are today one of the key research areas in computer science and healthcare application industries [9]. Indeed, wireless sensor networks for healthcare have emerged in the recent years, driven by the need to collect data about physical, physiological, psychological, cognitive, and behavioral processes in spaces ranging from personal to urban [167]. Pervasive healthcare systems are able to provide rich contextual information and alerting mechanisms against odd conditions with continuous monitoring.

Today, nano- and micro-networks of sensors enable health monitoring and logging vital parameters of patients. **Notable examples of the available sensors** [56, 177, 44] are: *tri-axis accelerometers*, to recognize and monitor body posture; *gyroscopes*, to measure or maintaining orientation; *glucose sensors*, to monitor the amount of glucose circulating in the blood (non-invasive glucose monitoring has been also investigated through infrared technology and optical sensing); *blood-pressure sensors*, to measure systolic and diastolic human blood pressure, utilizing the oscillometric technique; *oxygen and carbon dioxide* (CO_2) gas sensors, to monitor changes in CO_2 levels, as well as to monitor oxygen concentration during human respiration; *ECG sensors*, to obtain a graphic record of the electrical activity of the heart; *EEG sensors*, to measure the electrical activity within the brain (usually by attaching small electrodes to the humans scalp at multiple locations); *EMG sensors*, to measure electrical signals produced by muscles during contractions or at rest; *temperature sensors*, to measure the temperature of the human body; *humidity sensors*, to measure the humidity of the immediate environment around a person. The adoption of these advanced medical and environmental sensors enables networked systems (sometimes defined *smart e-health systems* [203]) to continuously monitor patients' physiological and physical conditions, and transmit sensed data in real time via either wired or wireless technology to a centralized location where the data can be monitored and processed by trained medical personnel. Often, state-of-the-art-solutions leverage cloud computing as it can provide a powerful and scalable storage and processing infrastructure to perform both online and offline analysis and mining of sensor data streams, also lowering management costs [101, 179, 252, 27].

Having in mind that e-health systems store and process very sensitive data, security and heterogeneity are commonly considered issues, as privacy and interoperability are common concerns [101]. Therefore, such systems should rely upon proper security and privacy mechanisms [213]. Network performance generates other challenges recent research is looking at. For instance, network congestion can cause degradation of the overall channel quality and loss rates to raise and leads to buffer drops and increased delays. In addition, it tends to be unfair toward nodes whose data has to traverse a larger number of radio hops [116].

4.5. (Wireless) Body Area Networks

A Wireless Body Area Network (WBAN) consists of intelligent devices attached on or implanted in the body, which are capable of establishing a wireless communication link. This term was first coined by Van Dam et al. [286] and received the interest of several researchers. As the development and research in the domain of WBANs is only at an early stage, the terminology is not always clearly defined. While *WBAN* is the term also adopted by IEEE [177], there are some variations that include the word *wireless* and/or the word *sensor*. As a result, *WBAN* and *WBASN* are commonly accepted acronyms.

WBANs are composed by different types of devices: (i) sensor nodes (in charge of responding to physical stimuli and gathering data on them, possibly processing and reporting this information—see section 4.4) and (ii) actuators nodes (acting according to data obtained from the sensors or interaction with users). In addition, (iii) a body control unit (BCU), i.e. a personal device—typically a smartphone or a personal digital assistant (PDA)—also known as *body gateway* or *sink* may gather all the information acquired by the sensors and inform the user via an external gateway, an actuator, or simply a display or a led on the device [177].

Communication protocols designed for WBANs can span from communication between the sensors on the body to communication from a body node to a datacenter connected to the Internet [177, 56]. **Taxonomies** proposed in the literature introduce *intra-BAN communications* (tier-1), *inter-BAN communications* (tier-2), *beyond-BAN communications* (tier-3) [56]. The term *intra-BAN* *communications* is adopted in reference to radio communications of about 2 meters around the human body, possibly sub-categorized as: (i) communications between body sensors, and (ii) communications between body sensors and the BCU acting as a personal server. Unlike WSNs that normally operate as autonomous systems, a BAN seldom works alone. Inter-BAN communications can be divided into two categories: *ad hoc* and infrastructure-based. Finally, tier-3 communication is intended for use in metropolitan areas.

Unlike conventional WSNs, WBANs have their own characteristics [44]. Typically, they are not deployed with redundancy as high as to tolerate node failures and thus do not require high node density. Most WSNs are applied for event-based monitoring, where events can happen irregularly. In contrast, WBANs are employed for monitoring human physiological activities, which vary in a more periodic manner. As a result, the application data streams exhibit relatively stable rates. Energy consumption is commonly considered as an open issue. A number of different standards for WBANs exist (e.g., Bluetooth Low Energy, UWB, Bluetooth 3.0, and ZigBee) as well as open and proprietary technologies (e.g., Insteon, Z-Wave, ANT, RuBee, and RFID).

WBANs represent a paramount technological joining link, enabling wearable sensing technologies to be leveraged in pervasive monitoring activities.

4.6. Internet of Things

The Internet of Things (IoT) can be considered as the interconnection of uniquely identifiable smart objects and devices (*things*) with advanced connectivity that goes beyond M2M scenarios within today's Internet infrastructure. Indeed, IoT is considered a civil disruptive technology, because of its potential widespread in everyday life due to the variety of the application fields [18].

The success of this paradigm is reshaping modern healthcare, with promising technological, economic, and social prospects: IoT can be the main enabler for distributed healthcare applications [66], thus having a significant potential to contribute to the overall decrease of healthcare costs while increasing the health outcomes, although behavioural changes of the stakeholders in the system are needed [66, 215]. In turn, healthcare represents one of the most attractive areas for the IoT [136, 36, 83, 74], potentially representing its killer application [40].

Medical, diagnostic, and imaging sensor devices supported by wireless technologies constitute a core part of the IoT [136, 83], although general-purpose smart devices such as smartphones or PDAs are leveraged in several applications [62, 136, 40, 277, 75, 95, 274, 192, 320]. In the healtcare field, IoT enables scenarios where machines with decision support systems interact and communicate among them. For instance, in an IoT environment, intelligent personal assistant can interact with other smart objects in order to gain new knowledge and awareness about their users [247]. Driven by wireless technologies, the resulting up-to-date healthcare networks are expected to enable real-time monitoring of physiological parameters, thus to support the care of chronic diseases, early diagnosis, and the management of medical emergencies [136].

Starting from the basic IoT paradigm, a number of **variations peculiar to the healthcare** has been also envisioned. The *Internet of Medical Things (IoMT)* [144] refers to applications enabled by a personal healthcare system and consisting of implantable and wearable sensors and devices connected to a personal health hub (e.g., a smartphone or smartwatch) that is connected to the Internet. The *Internet of Nano Things* (*IoNT*) [213] refers to the application of IoT in nanomedicine, that is expected to enhance human health in novel ways (preventive health, proactive monitoring, follow-up care, and chronic care disease management). IoNT-powered e-health systems will make health monitoring, diagnostics, and treatment more personalized, timely, and convenient. The *Wearable Internet of Things* (*WIoT*) [126] aims at creating an ecosystem for automated telehealth interventions. WIoT connects body-worn sensors to the medical infrastructure such that physicians can remotely perform longitudinal assessment of their patients. WIoT enables monitoring human factors including health, wellness, behaviors, and other data useful in enhancing individuals' everyday quality of life. The *Internet of m-health Things* (*m-IoT*) [141] envisions a connectivity model between low-power personal-area networks (leveraging e.g., 6LoWPAN) and evolving 4G networks, emphasizing the existing specific features intrinsic to the global mobility of participating entities. The *Internet of Health Things* (*IoHT*) results from the combination of mobile apps, wearables, and other connected devices [277]. It is based on context-aware professional-grade sensor medical devices that are *always on*. These smart devices are capable to

Table 4: IoT paradigm variations in the healthcare field proposed in the literature.

Paradigm variation	Acronym	Year	Paper
Internet of m-health Things	m-IoT	2011	Istepanian et al. [141]
Wearable Internet of Things	WIoT	2014	Hiremath et al. [126]
Internet of Nano Things	IoNT	2015	Omanović-Mikličanin et al. [213]
Internet of Health Things	IoHT	2016	Terry [277]
Internet of Medical Things	IoMT	2017	Jha [144]

learn, leveraging sophisticated cloud-based analytics. Table 4 summarizes the IoT paradigms variations proposed in the scientific literature.

IoT enables **healthcare implementation in various settings** such as (i) hospital acute healthcare rehabilitation systems, (ii) long-term supervision of chronic diseases or elderly care (e.g., in nursing homes), and (iii) in-home surveillance such as community healthcare or rural area monitoring that establish a network covering an area around a local community [175, 136, 241, 322]. In more particulars, IoT also allows to implement *Ambient-Assisted Living* (AAL), where an IoT platform powered by artificial intelligence address the healthcare of aging and incapacitated individuals in their place of living in a convenient and safe manner [82, 112, 140]. For instance, these systems advice patients and alert in real time doctors about their movements, changes of their vital parameters, or significant variations of environmental conditions, in order to take preventive measures [62, 75].

In more general terms, IoT enables patient remote health monitoring in all its facets: continuous monitoring of physical parameters [75, 250, 192] (also using wearable devices [25]), statistic data generation and diseases-risk drawing [95], verifying compliance with treatment and medication [136], management and prevention of diabetes and obesity (e.g., educating to and empowering good nutritional habits [294, 290] or fitness programs [66, 136]).

4.7. Cloud Computing

Cloud computing is a paradigm that enables the leasing of computing resources (such as computational, storage, and networking resources) in real time and with no upfront commitment by customers. It guarantees *pay-per-use* billing on a short-term basis, simplifies operation, and increases (computing and networking) resource utilization via virtualization, thus also allowing to implement economies of scale [17]. Cloud customers take advantage of the appearance of infinite computing resources on demand, thus leveraging and delivering *everything as a service* (e.g., Infrastructure, Platform, or Software as a Service—Iaas, PaaS, and SaaS, respectively) [158]. Both public- and private-cloud services exist: the former are available to the general public, while the latter are dedicated to a single organization. Hybrid solutions can be also implemented [194].

Cloud computing can significantly contribute to containing healthcare integration costs and optimizing resources. Economics, simplification, and convenience of the way computing-related services are delivered are among the main drivers of cloud computing [268, 22, 52]. Indeed, cloud computing offers a promising approach to satisfy the IT needs of the healthcare sector in a favorable way, simplifying health processes [90, 6, 229, 42, 151]. While the need for computation, storage, and networking resources are common drivers to the adoption of cloud technologies for general applications leveraging the IoT paradigm [36], analyzing papers relying on cloud technologies for healthcare-related applications we report in Table 5 the drivers leading to the the adoption of the cloud paradigm in typical healthcare scenarios.

Cloud computing is expected to play a big role in changing the face of health information technology thus benefiting healthcare research, improving healthcare services (enhancing their quality and outcomes for patients), and helping manage the current trend of growth in digital data and anywhere-and-anytime availability of medical services [6, 173, 36]. The term *Healthcare as a Service (HaaS)* has been coined to name the adoption of cloud technologies in the healthcare field [146, 158].

Cloud proved to be a very versatile technology. Table 6 reports a number of studies that leveraged the benefits of cloud computing to implement applica-

Table 5: Drivers to cloud adoption in healthcare-related scenarios.

Paper	Driver							
	Scalable processing	Scalable data storage	Easy data sharing	Easy data collection/integration	Enhanced reliability	Enhanced security	Enhanced service performance	Enhanced service availability
Bahga and Madisetti [20]	✓	✓		✓				
Benharref and Serhani [27]	✓	✓						
Biswas et al. [29]	✓							
Bourouis et al. [38]	✓	✓						
Chen [55]		✓	✓				✓	
Chen et al. [57]	✓	✓						
Chen et al. [61]		✓		✓				
Cimler et al. [63]	✓	✓				✓	✓	✓
Deng et al. [78]	✓	✓			✓		✓	
Doukas and Maglogiannis [83]								
Ekonomou et al. [88]		✓		✓				
Fan et al. [92]	✓	✓						
Fernández-Cardeñosa et al. [97]	✓	✓	✓					
Fernández et al. [96]		✓	✓					
Gachet et al. [104]	✓	✓						
Guo et al. [118]	✓		✓					
He et al. [122]	✓		✓					
Hossain and Muhammad [130]	✓							
Hu et al. [133]			✓					
Kanagaraj and Sumathi [154]	✓		✓					
Kaletsch and Sunyaev [152]		✓						
Kaur and Chana [158]			✓					
Li et al. [183]		✓	✓					
Rodriguez-Martinez et al. [240]				✓				
Shah et al. [252]	✓	✓	✓					
Sobhy et al. [258]		✓						
Wang et al. [300]	✓	✓						
Xia et al. [314]		✓						
Yang et al. [318]	✓	✓						
Wooten et al. [309]			✓					
Zhang et al. [324]		✓						

tions of different nature. A more detailed analysis of these applications is provided in Section 5. In general terms, cloud not only facilitates healthcare best practices, also it opens the door for more innovations to take place [22].

Table 6: Approaches, proposals, solutions, architectures, frameworks, systems, and platforms leveraging cloud computing for healthcare applications.

Class	Paper
Health / wellness monitoring	[29], [38], [63], [130], [158], [252], [300], [314]
Patients and hospitals data management	[20], [61], [91], [97], [96], [133], [154], [183], [240], [258], [313], [318], [118], [152], [122], [88]
Assisted living / Home healthcare	[55], [57], [78], [92], [27], [104]
Genomic analysis	[14], [79], [233], [327], [169], [212], [147], [110], [298], [218], [180], [48]

4.8. Fog Computing, Mobile Edge Computing, and Mobile Cloud

The proliferation of pervasive mobile devices generating big amounts of data to be stored and processed, together with virtualization and programmability technologies promoting the softwarized deployment of network functions, highly challenge the cloud. Indeed, in several contexts the cloud cannot meet all the requirements of healthcare applications by design and a new architecture is needed [109]. *Fog computing*, *mobile edge computing* (MEC), and *mobile cloud* paradigms as well as the *cloudlet* concept come into play to mitigate these issues.

Fog computing (introduced by Cisco [33]) deals with the transfer of the cloud computing services to the edge network, possibly integrating them with other users' device resources, thus delivering them in a distributed way between end devices and traditional cloud computing datacenters. According to the proposed ETSI standard [217], *mobile edge computing* provides IT and cloud-computing capabilities within the radio access network in close proximity to mobile subscribers. Fernando et al. [98] provided a comprehensive survey on *mobile cloud*, and proposed it as an umbrella term. Several definitions are provided for it: (i) running an application on a remote resource-rich server while the mobile device acts like a thin client; (ii) considering other mobile devices themselves as resource providers of the cloud making up a mobile peer-to-peer network; (iii) mobile devices offloading their workload to a local edge cloud. Finally, the idea of *cloudlet* developed by the Carnegie Mellon University [248] is introduced to refer to the middle tier of a 3-tier hierarchy (i.e. *mobile device–cloudlet–cloud*).

The purpose of fog and mobile edge computing is to run the heavy real-time applications at the network edge, directly taking advantage of the billions of connected mobile devices. Because a mobile device operates on a finite supply of energy contained in its battery, in the context of mobile clouds the cost of participation (i.e. power consumption) should be in proportion to the benefit gained. The main advantage in adopting these paradigms is the improvement of the quality of service: delay-sensitive applications face the problem of large latency, especially when several smart devices and objects are getting involved in human's life (see section 4.6). For instance, fog computing leads to more predictable service delivery with low response time, avoiding delays and network failures that may interrupt or delay the decision process and healthcare service delivery [13, 253]. Mobile cloud also enables systems to use contextual information to automatically change their configurations to adapt to the context, provides personalized services and also mechanisms such as those to rectify low quality of service problems [98].

4.9. Big-data analytics

Large amounts of heterogeneous medical information have become available in various healthcare organizations, since smart and connected healthcare devices are increasingly adopted and contribute to generating streams of structured and unstructured data. Thus, today healthcare practitioners are commonly facing difficulties related to managing and capitalizing this data to their advantage. Accordingly, the implementation of big-data analytics in the healthcare field—that is the process of examining these large data sets to uncover hidden patterns, unknown correlations, and other useful information—is more and more attracting the interest of the scientific community, as this data would become useless without proper data analytics methods [16, 53].

Advances in big-data analytics help naturally transform research questions from being *descriptive* (e.g., *what has happened?*) to *predictive* (e.g., *what could happen?*) and *prescriptive* (e.g., *what should we do then?*) [51]. For instance, big-data analytics in healthcare can contribute to evidence-based medicine, genomic analysis, pre-adjudication fraud analysis, device remote monitoring, and patient-profile analyses. Big-data analytics can effectively reduce healthcare concerns, such as the selection of appropriate treatment paths and the improvement of healthcare systems [143]. More in general, big data technologies will reduce waste and inefficiency in clinical operations, public health, research and development [234, 204].

In healthcare-realated scenarios, three **main data sources** can be identified [191]: (i) *traditional medical data* originated from the legacy health system; (ii) *omics data*, which refer to large-scale datasets in the biological and molecular fields (e.g., genomics, microbiomics, proteomics, metabolomics, etc.) [59, 206]; (iii) *data from social media* (see Section 4.11), essentially consisting of signs and behaviors of how individuals and groups of individuals use the Internet, mobile applications, sensor devices, wearable computing devices, or other technological and non-technological tools to better inform and enhance their health. Therefore, healthcare-related big data can come from both *internal sources*, such as electronic health records, clinical decision support systems, and *external sources*, such as government sources, laboratories, pharmacies, insurance companies, and health maintenance organizations. Accordingly, data often comes in *multiple formats* (such as flat ASCII/text files, comma-separated values, relational tables, possibly encoding records reported in Section 3) and resides at multiple locations, in numerous legacy and other applications [234]. Further examples of sources and data types are reported in the following: unstructured and semi-structured human-generated data such as EMRs, physicians notes, email, and paper documents; big transaction data from healthcare claims and other billing records increasingly available in semi-structured and unstructured formats; biometric data, such as fingerprints, handwriting, retinal scans, x-ray, 3D, and other medical images, blood pressure, pulse and pulse-oximetry readings; machine-to-machine data readings from remote sensors, meters, and other vital sign devices; publicly available genetic-sequence databases; web and social media data, such as click streams and interactions from Facebook, Twitter, LinkedIn [234] (e.g., see Section 3, Section 4.2, Section 4.3, Section 4.4, Section 4.5, and Section 4.6).

All these characteristics being given, the enormous amount of healthcare data satisfies the **requirements to be qualified as big data**, due to its volume, velocity, and variety [234]. For what concerns *volume*, the newer forms of data, (e.g., 3D imaging, genomics, and biometric sensor readings), are fueling the exponential growth of the already daunting volume of existing healthcare data. While traditional healthcare data consists of static-paper files, x-ray films, and scripts, *velocity* of mounting data has increased with regular monitoring processes (e.g., multiple daily diabetic glucose measurements, more continuous control by insulin pumps, blood pressure readings, and Electrocardiograms). In addition, constant real-time monitoring is of the utmost importance in many medical situations (e.g., trauma monitoring for blood pressure, operating room monitors for anesthesia, bedside heart monitors, etc.). Finally, the enormous *variety* of data—structured, unstructured, and semi-structured—is evident and makes healthcare data both interesting and challenging.

Furthermore, healthcare-related big data, analytics, and outcomes have to be error-free and credible, thus being in line with the fourth characteristic introduced by some big-data practitioners and researchers: *veracity*, (i.e. data assurance), often considered a goal and not yet the reality [234]. Finally, enormous *value* (often seen as the fifth V) is envisioned in the predictive power of big data, due to recent results in fields such as public health, science, and medicine where the combination of omics and clinical data is expected to fuel precision and personalized medicine understanding the mechanisms of diseases and accelerating the individualization of medical treatments [65, 53].

Data mining—possibly defined as the analysis of large observational data sets to find unsuspected relationships and to summarize the data in novel ways that are both understandable and useful to the data owner—helps researchers gain both novel and deep insights and can facilitate unprecedented understanding of large biomedical datasets [321]. Mining algorithms are classified into two categories: *descriptive* (or *unsupervised learning*) and *predictive* (or *supervised learning*). Existing machine-learning algorithms (for e.g., data filtering, classification, clustering, association, and combination) can be adopted, although some existing shortcomings exist and have to be considered [235, 321].

The successful application of data mining provides novel biomedical and healthcare knowledge which can be effectively used to support clinical decision-making (e.g., the process of diagnosis, choice of treatment options, prognosis prediction) as well as administrative decision-making (e.g., staffing estimates, insurance, demographic and market trends, quality assurance, process efficiency, etc.) in healthcare delivery.

4.9.1. Tools and platforms for healthcare big-data analytics

New-generation technologies and architectures are required to extract value from larger and larger volumes of a wide variety of data by enabling high-velocity capture, discovery, and analysis [65]. This is driving to a shift in computing architectures needed to handle both the data storage requirements and the heavy server processing required to analyze these large volumes of data in a secure manner [65].

Raghupathi and Raghupathi [234] consider Hadoop and related technologies as the most significant for big-data analytics in healthcare, as enabling researchers to leverage data sets that were traditionally impossible to handle.

Both Raghupathi and Raghupathi [234] and Zou et al. [330] list a number of platforms and tools for big-data analytics in healthcare. The *Hadoop distributed file system* (HDFS) [254], is used to manage the data, dividing it in smaller parts and distributing it among different clusters. *Map Reduce* [76] is a programming model providing the abstractions to the distributing of sub-tasks and gathering results. Zou et al. [330] and O'Driscoll et al. [210] survey bioinformatic applications based on Map Reduce that can be employed in the next-generation sequencing (such as, mapping, assembly, gene expression, SNP analysis, and NGS data quality assurance) and other biological domains, providing a categorisation of bioinformatics projects based on the Hadoop platform.

Furthermore, many platforms are cloud-based, making them widely available [234]. Numerous vendors including AWS, Cloudera, Hortonworks, and MapR Technologies distribute open-source Hadoop platforms. Many proprietary options are also available, such as IBM's BigInsights. While the available frameworks and tools are mostly open source and wrapped around Hadoop and related platforms, there are numerous trade-offs that developers and users of big-data analytics in healthcare must consider [234].

Cloud storage is seen as the only affordable solution to provide the elastic scale needed for DNA sequencing, whose rate of technology advancement could now exceed Moore's Law [65].

Pipelines to deal with increasing amounts of omics data will be needed to store, transfer, analyze, visualize, and generate short reports for researchers and clinicians [5]. Cloud computing opens a new world of possibilities for the genomics industry to transform the way it approaches research and medicine: an entirely new genomics industry could result from Cloud computing, transforming medicine and life sciences [65]. Other solutions to deal with big data include the use of graphics processing units (GPUs) [65].

4.10. Artificial Intelligence and Soft- and Cognitive-Computing Techniques

As the rational thinking of healthcare practitioners involves a lot of subjective decision making, its complexity often makes traditional quantitative approaches of analysis inappropriate. Computer-based intelligent decision making systems can appropriately handle both uncertainty and imprecision, thus helping for early diagnosis of diseases.

Artificial Intelligence (AI) is the simulation of human intelligence processes by computer systems. These processes include *learning*, (i.e. the acquisition of information and rules for using the information), *reasoning* (i.e. using the rules to reach approximate or definite conclusions), and *self-correction*. At the forefront of the techniques of AI rapidly advancing in healthcare scenarios are natural-language processing [103, 45], pattern recognition [172], and machine learning [231], that can be applied to many specific fields, such as biomedicine and life sciences [65].

Artificial intelligence can lead to the development of tools to assist clinicians and potentially improve patient outcomes [168]. Fuzzy logic can be leveraged to reproduce medical decision making process in decision support systems [246]. Indeed, machine learning applied to routinely captured clinical data can generate new information and potentially new insights that are missed by clinicians. For instance, the huge volume of ongoing ECG patterns cannot be monitored by human operators, but requires proper strategies to be efficiently analyzed and make available the best-possible patient-care decisions.

Because of the huge quantity of data generated at high rates in healthcare domain, the ability to extract the *relevant information* is of the utmost importance for the effective treatment of patients as well as the diagnosis and the prediction of diseases. In this context, **soft computing**—that is a collection of problem-solving technologies that can adapt to the problem domain, such as *probabilistic reasoning*, *fuzzy logic*, *neural networks*, and *genetic algorithms*—provides promising solutions and better results in comparison to traditional approaches. It aims at exploiting the tolerance for imprecision and uncertainty to achieve tractability, robustness, and low solution cost [32]. Gambhir et al. [105] propose a taxonomy of soft-computing techniques presented for diseases diagnosis and prediction. Nowadays, their application is also increased gradually in diverse areas of medical services (e.g., helping the medical expert, owing to effectiveness and continuous improvement of classification and detection system, and upgrading diagnostic rate [105]).

Technologies such as **cognitive computing** (an evolution in computing that mimics some aspects of human thought processes on a larger scale) try to fill the growing gap between the huge amount of data available and the fraction being effectively integrated, understood, and analyzed [60]. They address data challenges applying multiple technologies, to enable comprehension of disparate data sources. For instance, cognitive solutions can be trained to understand technical, industry-specific contents (scientific publications as well as structured databases or lab values) and use advanced reasoning, predictive modeling, and machine-learning techniques to advance research faster. Current projects suggest that cognitive computing infuses novelty and adds speed to the research process. IBM Watson [60], is a cognitive computing technology, possibly configured to support life sciences research.

Cloud-based solutions are often implemented to help manage and access data (e.g., images), as well as enhance efficiency addressing the growing demand of real-time computation and analysis [318, 154, 151, 130].

Artificial intelligence solutions strongly support image analysis as well as voice and speech recognition, thus enabling a variety of applications. For instance, the elaboration over speech and face images allows to to detect patients' state [130]. In the context of cataract classification and grading, Guo et al. [117] investigate the wavelet transform and the sketch based methods to extract additional knowledge from fundus images, helpful for improving the screening test of cataract in underdeveloped areas without sufficient healthcare resources.

Thanks to speech recognition man-machine dialogue can be implemented [57], expanding the application scope of purposely designed robots (see Section 4.12). Services for building conversational interfaces into applications using voice and text (such as Amazon Lex [12]) provide advanced deep-learning functionalities of automatic speech recognition for converting speech to text, and natural language understanding to recognize the intent of the text. These services enable health companies to quickly make voice or text-based chat interfaces for their apps, making them interactive. Therefore, progress in AI also leads to the implementation of *chatbots* allowing users to type a question into messaging apps any time and receive free responses from doctors. Thanks to these apps, users are also able to see responses from doctors to questions that are similar to their own [35, 124].

However, downsides of the adoption of AI in the health domain have been also identified. In a recent editorial, Beam and Kohane [26] discussed the opportunities presented in translating AI into clinical care, reporting how the AI field has failed to deliver on its promises of automated and improved disease detection, more effective monitoring, and efficiency boosts in workflow, despite several decades of research and hype [168]. *Overdiagnosis* is another growing problem, generated by technical improvements in the sensitivity of detection methods. It may lead to patient anxiety and harm from further testing and unnecessary treatment [168].

4.11. Social network analysis and social media

The analysis of *social networks* is an interdisciplinary academic field which emerged from social psychology, sociology, statistics, and graph theory. The social network perspective provides a set of methods for analyzing the structure of social entities as well as a variety of theories to explain these structures, whose study may lead to identify local and global patterns, locate influential entities, and examine the dynamics of the network [302].

Social media (also social networking services) are online platforms that are used by people to build social networks with other people who share similar interests, activities, backgrounds, or real-life connections.

Although slower to adapt to the changing trends, the field of healthcare is starting to embrace social

media, thus allowing medical providers to communicate with patients in ways they never could before [304]. Social media implemented through web-based, mobile, and cloud applications and providing real-time access are changing the way healthcare practitioners review medical records and share medical information. Social media frameworks enable healthcare practitioners and professionals who look after patients to easily collaborate both in and out of the hospitals [266]. According to recent surveys, social media are changing the nature of health-related interactions [261]. For instance, social media also influence patients' choice of hospital, medical facility, or doctor [304, 261]. More in general, social media technologies are changing the practice of medicine and are expected to shape the future of healthcare [304].
The potential **benefits** of social-network analysis in the field of medicine are vast and are growing every day. For instance, graph theory and social network measures on healthcare data help understand chronic disease progression [161]. This kind of information may be leveraged to enable preventive measures as well as reduce cost and health risk, thus further benefiting both providers and patients [161]. Key players in the health sector can be identified, information flows can be analyzed and documented. Indeed, experience of knowledge management in non-healthcare organizations can offer useful strategies and insights for implementing evidence-based practice in healthcare [50]. *Inter-hospital collaborative networks* are becoming a common organizational strategy to deal with uncertain and dynamic environments, with varying performance results [164].
Paired with aforementioned potential benefits, social media present several **problems and open issues**, that are not often obvious at first glance. It is worth noting, as an example, how the typical small size of the networks studied in the healthcare area may severely impact metrics calculated during graph analyses as these are sensitive to the number of people in the network and the density of observed communications [86]. Therefore, specific methodological bases are needed to obtain greater rigour [86]. On the basis of this information, impact of potential improvements can be evaluated [68].
Moreover, while the ability provided by social media to send messages, monitor statuses, and receive suggestions from friends and not just by medical personnel and other care providers, potentially make these communication systems less repulsive, *social barriers* to the implementation of these novel approaches do exist. Although the category of elderly patients can use social-media systems, recent studies reported how patients may be afraid of these new technologies [198].
Problems of **security and privacy** are being constantly raised [196, 269], as *m-health social network* has been increasingly adopted by healthcare providers all over the world. For instance, social network sites if used inappropriately can have great implications for healthcare professionals, as they are changing the way information is shared due to the great number of users. The most felt issue is related with the breach of privacy or confidentiality against patients, but other issues can arise as well [174]: lateral violence against colleagues, boundary violation (when the professional relation doctor-patient or caregiver-patient starts blurring into personal relationship), employer use of social media against employees (including prevention of career advancement or hiring due to social media content deemed inappropriate).
Besides the misguided usage of social media, technical issues arise regarding security and privacy of service usage (exploitable by *malicious third parties*). In order to solve these problems, secure and privacy-preserving key management schemes resilient to mobile attacks have been proposed, e.g., leveraging the cooperation of the mobile patients in the same social group for both hierarchical and distributed environment [329].

4.12. Robotics

Systems—even on a micrometer or nanometer scale—are included in the area of robotics if they perform all three essential functions defining a robot: (i) *acting on environmental stimuli* in combination with (ii) *sensing* and (iii) *logical reasoning* [37]. Accordingly, systems with no mechatronic actions (such as computer and information systems like expert systems, intelligent databases, or artificial intelligence systems) are commonly not regarded as robots.
Robotics for healthcare is an emerging field, that is expected to grow due to population aging, healthcare personnel shortages, and the need for higher quality care (e.g., high precision surgery). Indeed, it is often envisioned as a key component in a number of healthcare scenarios.
For instance, a **mobile robotic nurse** assistant is highly desired to enhance the efficacy and quality of

care that nurses and paraprofessional staff can provide [132], both in a hospital ward and when providing assistance to old-aged people under direct and telepresence control by a nurse or physician [57, 70]. Safe and robust robotic systems are required, in order to work effectively in a critical environments such hospitals [132]. Several features are typically needed, also depending upon the specific working environment of the robot. These features may include [57, 132]: (i) *flexible motion control* (e.g., providing all around motion, turning motion, circling motion, and speed control); (ii) *route planning* (i.e. autonomously moving to the target point under complex and unpredicated environments, and avoiding obstacles is one of the most fundamental and important capacities of the robot); (iii) *network connection*; (iv) *automatic protection* of the robot (e.g., with the infrared and ultrasound sensors) to guarantee the safety of the robot during movement; (v) *entertainment* (e.g., software to cure diseases suffered by elderly people such as those to relieve senile dementia). The adoption of robots for healthcare applications is expected to reduce hospital costs and ameliorate problems posed by the shortage of nursing staff.

A long-time and still evolving application of ICTs to healthcare is the **surgical robot** (also in teleoperator setups). Surgical robots are an established tool for surgical operations that are minimally invasive and require extreme precision of movement, hard to achieve with directly hand-operated tools. Being electronically mediated, the commands given to surgical robots can be also transmitted by a remote operator (and the visual and tactile feedback sent to the operator), allowing **teleoperation** when the surgeon can not be physically present with the patient: suitable telecommunication infrastructure is needed to guarantee the strict service requirements of the operator–robot communication [89].

A well-established case of telemetry (a prerequisite for teleoperation) applied to healthcare is the **wireless capsule endoscopy** [297], a device that has greatly improved the diagnostic capabilities as well as the comfort of the patient for digestive endoscopy: a swallowable pill-shaped camera transmitting—via wireless body area network—images of the gastrointestinal tract to a receiver (worn by the patient during normal daily activities). While the endoscopy usage is nowaday established, research is ongoing to equip the capsule with active locomotion and therapeutic modules, thus turning it in a teleoperator [64].

Remote commands (and the context that prompted them) can in principle be learned and independently reproduced by the robot: current research investigates the adoption of Artificial Intelligence to add more advanced functionality beyond the dexterity augmentation currently provided [157]. First-generation surgical robots are now being adopted as a basis for open-source research projects aiming at investigating control algorithms for teleoperator setups [159].

Independent robots that perform more routine tasks (such as administering injections or taking blood samples) are also being designed, requiring complex real-time processing of multiple information sources (near infrared and ultrasound imaging, and force guidance) [21].

Other examples of applications of robotics to healthcare regard new generation **prosthetics**. Various forms of prosthetics have been enhanced with increasing semi-autonomous capabilities, reducing the need of external operation, or even of detailed and explicit commands, approaching a "smart" behavior in response to inputs from the patient and the environment. Powered and smart wheelchairs represent a notable example of this trend [111]. The communication between the patient's brain and the robotic prostheses also has been subject of fruitful research [10].

In the last decade the first commercial applications of robotics to healthcare have just begun to be adopted, and new laboratory prototypes are functional and in search for a market supporting their industrialization: in the near future, the impact of robotics on healthcare is expected to experience further intense growth along these very promising lines.

4.13. 3D printing

3D printing can be defined as the process of creating three-dimensional solid objects from digital files using a computer-aided design (CAD) program [278]. There are three commonly used **methods of adding the material in layers** [190, 278]: (i) *Fused Deposition Modeling* (FDM) consists in using plastic coils or metal filaments that are melted by a heated nozzle to form layers of material that hardens into the solid object. (ii) *Selective Laser Sintering* (SLS) fuses small particles of plastic, metal, ceramic, or glass powder into a 3D mass using a high-power laser. (iii) *Stereolithography* (SLA) uses an optical light energy source to scan over a vat of light curable resin, solidifying specific

areas on the surface of the liquid. FDM and SLS are most widely used processes [278], but according to Malik et al. [190], FDM is used in most economical consumer printers and only occasionally in medical applications.
The resolution of a 3D printer limits the size of the smallest feature the printer is capable of producing, and is also a function of the structural strength of the materials used [39].
3D printing allows the rapid and inexpensive production of small parts for laboratory work. 3D printing technology generates a number of different opportunities in the health domain, as 3D printing structures are popular and used as key components of products [93]. The rapid prototyping capability offered by 3D printing is also considered advantageous for commercial applications. As patients understanding of their medical condition and treatment satisfaction has gained increasing attention in medicine, 3D printing may play a role in patient education, e.g., to facilitate patient's pre-surgical understanding of their tumor and surgery [28].
Robotic 3D bio-printers, consisting in multiple print heads (e.g., for human cells and hydrogel) and managing bio-ink to create layers of cells to build tissues are also becoming commercially available [214]. In this context, monitoring health of 3D structures is particularly important (e.g, through sensors embedded inside a 3D structure itself).

5. ICTs-based Health Application Scenarios

Both the scientific literature and the market-evolution trends show how the healthcare is potentially one of the killer applications for ICT.
Guided by the scientific literature, in this section we provide an overall view on the applications stemming out in recent years thanks to the evolution in technological achievements.
While this section is not aimed at providing an exhaustive view overall every possible healthcare application supported by ICTs, here we discuss the main healthcare scenarios enabled by the fruitful convergence of the ICTs pillars and paradigms introduced in Section 4.
In more details, in the following we focus on *health-monitoring applications* (Section 5.1), *genomic analysis* (Section 5.2), *information system for collecting and sharing medical data* (Section 5.3), and *personalized-health solutions and preventive-medicine applications* (Section 5.4).

5.1. Health and wellness monitoring

The combined evolution of mobile technologies (e.g., smart and wearable devices), WSNs and WBANs, wide-area communication infrastructures, together with the evolution of the IoT paradigm, as well as of supporting technologies—such as cloud computing or big-data analytics—is paving the way for the deployment of innovative healthcare pervasive monitoring applications [252, 247]. These solutions are carrying unprecedented opportunities for personalized health and wellness monitoring and management, allowing for the creation and the delivery of new types of cloud services [149, 24], that can either replace or complement existing hospital information systems [171].
According to Patel et al. [219], systems for patients' remote monitoring consist of three main building blocks: (i) the sensing and data-collection hardware to gather physiological and movement data—ranging from tiny biosensors to battery-free RFID tags; (ii) the communication hardware and software to relay data to a remote center; and (iii) the data analysis techniques to extract clinically-relevant information from physiological and movement data.
Several monitoring solutions gather clinical information (such as position, temperature, or breath frequency) via body sensors or mobile devices, and integrate it in the cloud, leveraging seemingly infinite storage, scalable processing capability as well as high service availability [247, 209, 279, 317, 29, 252, 130, 38, 242, 101]. Often, the cloud represents a flexible and affordable solution to overcome the constraints generated by either sensor technologies or mobile devices and therefore a growing number of proposals takes advantage of the cloud capabilities to remotely offload computation- or data-intensive tasks [312, 63, 324, 283, 55, 300, 207, 83, 296] or to perform further processing activities and analyses [281, 326]. Depending on the type of sensors adopted, applications can be clusterized in *in-body* e *on-body* [285].
The literature also shows how the IoT paradigm is able to provide a valuable framework to support health monitoring, especially for what concerns the collection of health records, potentially providing the generation of statistical information related to health condition [176, 284, 84, 320, 213, 323]. It is worth noting how this guarantees to rapidly lower the risk of introducing errors if compared to methods requiring manual intervention [74]. IoT devices can be used to monitor users' health status and

transmit the data directly to remote datacenters taking advantage of the cloud computing paradigm. This direct interconnection of the large amount of devices for remote storage, processing, and retrieval of medical records in the cloud demands a reliable network connection imposing many challenges related to network connectivity and traffic [13]. With the aim of mitigating these challenges and enhancing health monitoring systems, Gia et al. [109] and Shi et al. [253] propose to exploit fog computing at smart gateways, providing advanced techniques and services such as embedded data mining, distributed storage, and notification service at the edge of network in order to overcome issues generated by the adoption of remote cloud services.
According to the specific goals, monitoring applications found in the literature can be categorized as follows.

5.1.1. Telepathology, medical-status and disease monitoring

Many contributions are available in the literature that shows how ICTs are able to support a number of different applications, primarily related to telepathology, telemedicine, and disease monitoring [205, 56].
First noticeable attempts date back to eighties, when the integration of robotic microscopy, video imaging, and broadband telecommunications was envisioned to have great potential to serve as the infrastructure for supporting telepathology services [306]. As of today, there exist both studies on generic frameworks applicable to the majority of use cases [49] and works focused on specific diseases, such as cardiovascular diseases [145], diabetes [299], cancer detection, Parkinson [160], asthma, and Alzheimer [163].
The outcome of these monitoring systems can both feed large scale studies and drive methodologies tailored according to the results of the specific individual.

5.1.2. Medication intake monitoring

Medication-intake monitoring addresses medication noncompliance, that is common in elderly and chronically ill subjects, especially when cognitive disabilities are encountered.
One of the early prototypes developed by Moh et al. [201] aims to control the medicine intake of the elderly with the combined use of sensor networks and RFID. Since in drug treatments, the timing of drug delivery is crucial for achieving the optimal treatment effectiveness and minimizing adverse effects, today several apps are available that provide prescription reminder that features prescription alarms, reminder scheduling, setup reminders, and medication intake tracking [256].
Advanced solutions are also today commercially available. For instance, *Proteus Discover* [232] consists of ingestible sensors, a small wearable sensor patch (measuring activity, rest, and hearth rate), an application on a mobile device, and a provider portal. Once the sensor reaches the stomach, it activates the sensor patch and a digital record is sent to the cloud through the mobile device. It provides insights on patient health patterns and medication treatment effectiveness, leading to more informed healthcare decisions for everyone involved.
These systems provide a quantitative way of assessing treatment efficacy and are a valuable tool for clinicians in disease management [219].

5.1.3. Rehab

WBAN technologies are very useful in detecting and tracking human movement for *home-based rehabilitation*. Sensor diversification, multi-sensor data fusion, real-time feedback for patients, and virtual-reality integration are examples of features that make rehabilitation a specific research area with specific constraints and requirements [328, 205].
WBANs also enable *self remote monitoring of human body and biofeedback*, i.e. the measurement of physiological activity plus other potential useful parameters and feed them back to the users, allowing them to learn how to control and modify their physiological activities with the aim of improving their health and performance [205, 222, 43, 238].

5.1.4. Assisted living

As the healthcare costs are increasing with the world population aging [215], several countries are promoting *aging in place* programs allowing elderly and individuals with chronic conditions to remain in the home environment while they are remotely monitored for safety and for facilitating the implementation of clinical interventions [219].
Telepresence and videoconferencing robotic solutions (e.g., equipped with computer monitor and built-in webcam and remotely controlled over the Internet) have been also proposed [70]. This kind of solutions have the advantage of being able to better connect older people with distant relatives

without getting out of bed, or needing to learn new technologies.

WBANs are of the utmost importance for these assisted-living facilities. Indeed, the health condition of elderly and people with disabilities can be estimated from their heart beat rate, blood pressure, and accelerometer data.

Wearable sensors are often combined with ambient sensors (*ambient-assisted living, AAL*) when subjects are monitored in the home environment [219]. Ambient sensor networks can sense and control the parameters of the living environment and then deliver the body data to a central station. State-of-art artificial intelligence methodologies are possibly used to develop *ambient-intelligence systems* in the healthcare domain, including learning, reasoning, and planning techniques [3]. Examples of instrumented environments include sensors and motion detectors on doors that detect opening of medicine cabinets, refrigerators, or home front doors. WiFi signal strength can be also leveraged for tracking position [85]. In order to increase context awareness for increasing system efficiency, location tracking can be also extended to outdoor scenarios (e.g., for assisting people with cognitive disabilities or identifying the locations of people when an alarm situation has occurred). In these cases, GPS is the most robust and widely available technique [9].

Although falls and body movements are specific cases of activity classification, there is a significant research effort focusing on fall detection, gait analysis, and body posture. Indeed, accidental falls are among the leading causes of death over 65 [9]. Issues exist in fall identification with acceleration data, as differentiating a fall from other fall-like situations like jumping, lying or sitting down quickly on a chair is not trivial. Usually, proposed solutions make use of accelerometers and gyroscopes for identifying sudden falls. There are only few studies that propose the use of unobtrusive ambient video cameras, because of the descending privacy issues. Alternate approaches integrate fall detection to posture analysis, e.g., after a hip replacement operation [137].

This kind of monitoring systems may be connected to a healthcare center for observation and emergency assistance, in case of strong changes in the observed parameters or deviations from the normal range [3].

Cloud capabilities also allow to implement frameworks to collect patients' data in real time and perform appropriate non-intrusive monitoring to propose medical and/or life style engagements [314], thus to support pervasive healthcare and AAL [57, 78, 104].

5.2. Genomic analysis

The progress of high-throughput sequencing technologies (NGS) is producing biological big-data sets whose volume is growing exponentially and continues to expand as the cost of sequencing decreases. This is causing the classical computational infrastructures for data processing to become ineffective and difficult to maintain. Cloud technologies offer straightforward solutions to the issues deriving from storing big genomics data, processing it in a timely manner, and subsequently analyzing the data for meaningful deductions [42, 47, 210].

Entering both the datasets and software into the cloud and providing them as a service replacing in-house solutions, allows to get a level of integration that improves the analysis and the storage of bioinformatics big data and enables a new area of systems biology [210].

Knowledge of DNA sequences has become indispensable for basic biological research and in numerous applied fields [47], such as comparative genomics (including metagenomics [308, 14, 79, 233, 327, 169], ribosomal RNA (rRNA) classification [212], infectious disease diagnostics [147]), genome analysis and SNP Research (including diagnostic approaches and prevention [110], analysis structure of mutant proteins [298], variant pathogenicy assessment [218]), regulation of gene expression (e.g., role of messenger RNA (mRNA) and non-coding RNAs (ncRNA) [180, 48]), early detection of cancer, forensic biology, and virology.

NGS cloud solutions are at an early stage and there is still a long way to go, as they lack evolved PaaS for the development of new emerging SaaS. Moreover, most of existing NGS tools must be translated in SaaS form [47].

Advancements in genomics and personalized medicine not only affect healthcare delivery from patient and provider standpoints, but also reshape biomedical discovery. Data mining efforts are also attempting to uncover non-intuitive phenotypic links between drugs and clinical or cellular side effects, e.g. discovering the causative genes and pathways [316], and associating chemistry or biological pathways with molecular and clinical side effects [138].

Table 7: Healthcare cloud-based information systems (in chronological order).
Legend:
●: the paper focuses on the aspect;
◐: the paper partially deals with the aspect (only discussed or left as future work);
○: aspect not taken into consideration.

Paper	Year	Data format	Security	Privacy	Performance
He et al. [122]	2010	hospital information	○	○	○
Yang et al. [318]	2010	EMR + medical images	○	○	●
Kaletsch and Sunyaev [152]	2011	PHR	○	●	○
Li et al. [183]	2011	EMR	○	●	○
Kanagaraj and Sumathi [154]	2011	medical images	◐	◐	○
Ekonomou et al. [88]	2011	EHR + PHR	●	●	○
Rodriguez-Martinez et al. [240]	2012	EHR + billing info	◐	◐	○
Fernández-Cardeñosa et al. [97]	2012	EHR	○	◐	○
Wu et al. [313]	2012	EHR	◐	●	○
Chen et al. [61]	2012	EHR	●	●	○
Sobhy et al. [258]	2012	EHR	●	●	○
Hu et al. [133]	2012	EMR	◐	◐	●
Guo et al. [118]	2012	*unspecified (generic)*	◐	◐	○
Fernández et al. [96]	2012	MHR	◐	◐	○
Bahga and Madisetti [20]	2013	EHR	●	●	○
Fabian et al. [91]	2015	EMR	●	●	○

5.3. Cloud-based information systems

Cloud solutions have been largely adopted to both improve and simplify the design, the development, and the deployment of a number of information systems, designed to collect, process, and share medical data such as clinical records [91, 118, 182, 268, 92, 183, 318, 258, 309, 20, 61, 96, 97, 133], hospital administrative information [240], or medical images [122, 154, 229, 84, 151].

These platforms are intended to simplify the information sharing process across different medical structures [122, 183] or between hospitals and patients [183, 182].

The data collection process is also benefited, when the involved entities are provided with mobile user interfaces to cloud services for gathering and managing healthcare information [84].

Table 7 briefly summarizes the proposals found in the literature that leverage cloud computing to implement healthcare information systems. As shown in the table, the majority of the proposals is devoted to manage data in EHR format [88, 240, 97, 313, 61, 258, 20]. In several cases these systems also aim at integrating data in several different formats [318, 88, 240]. The table also highlights the specific aspects that are the focus of each study. As shown in the table, the majority of studies took into consideration both security and privacy aspects, that are both often considered as critical. Moreover, since 2011 a general trend of increasing interest is observed for these two aspects. On the other hand, concerns about the performance of the systems to be implemented are addressed only in few cases [318, 133].

5.4. Personalized-health solutions and preventive medicine

Big data is paving the way to **personalized healthcare**, both at individual and population level [138, 293, 53]. Implementing this approach, leads to reduce healthcare-related costs (more than $300 billion savings per year in US healthcare [94]) as big data are helpful to detect fraud, abuse, waste, and errors [265, 235].

The adoption of big-data analytics is leading to shift from cure to **prevention** [235]. For instance, big-data analytics could help prevent disease by identifying modifiable risk factors and designing interventions for health behavior change [191]. Within neonatal intensive care units, big data is effective to support a new wave of clinical discovery, leading to earlier detection and prevention of a wide range of deadly medical conditions [193]. In the field of system medicine and pharmacology, big-data analytics is helpful for predicting empirical drug-target signatures, also placing predictions using information from external databases [138, 72]. Processing data from EMR potentially aids in the discovery of new therapeutic targets when coupled with patient-derived omics data, providing holistic systems view of a patient and highlighting patient-specific changes for personalized pharmacology [46].

6. Using ICTs in the Health Domain: Issues and challenges

Supported by the analyzed literature, we believe innovative approaches and technologies are dramatically transforming healthcare, that is moving from reactive and hospital-centered to preventive, proactive, evidence-based, person-centered and focused on well-being rather than disease. The pervasive adoption of ICTs is pivotal for each of the mentioned transformations. Cutting-edge ICTs also provide the tools for addressing the complexity of challenging health problems (e.g., cancer, heart diseases, diabetes, neurological degeneration, etc.), and carries promises to accelerate discovery, improve patient outcomes, and decrease costs.

Together with promises, new constraints arise for effective solutions from the new clinical and medical needs, but also from new social interactions and barriers to behavioral change; finally new technologies dealing with healthcare face issues such as the heterogeneity of data and semantic mismatch. Therefore the solutions to be implemented strongly demand multidisciplinary teams, able to address technical, behavioral, and clinical issues.

In addition, innovative approaches are required to address delivery of high quality, economically-efficient healthcare that is one of the key economic, societal and scientific challenges worldwide. Several funding agencies and programs worldwide witness the interest in developing *next generation healthcare solutions* and encourage research communities to focus on novel disruptive ideas in a variety of areas of value to healthcare. This kind of solicitations are aligned with the visions calling for major changes in wellbeing and healthcare delivery, and are aimed at the fundamental research to enable the change. Again, the multidisciplinary nature of the challenge will require well-coordinated research efforts that draw not only from medicine, biology,

and engineering, but also from computer and information sciences as well as from social, behavioral, and economic sciences.
Focusing on the technological aspect that is addressed in this work, the adoption in the health scenario of ICTs reported in Section 4 amplifies a number of typical information and communication issues, extending them to this critical domain. The most recurring and hottest challenges raised by the adoption of ICTs emerging from the study of the surveyed scientific literature are related to:

- security;
- privacy;
- design;
- performance;
- efficiency;
- heterogeneity;
- interoperability;
- regulatory and legal issues.

After having identified the challenges above, we have opted for organizing them in an organic way, grouping the issues in this section as follows: Section 6.1 discusses *security* and *privacy*, as these aspects are strictly related; *design*, *performance*, and *efficiency* issues are discussed in Section 6.2, as they heavily impact each other; Section 6.3 deals with heterogeneity and interoperability, as the former is the primary cause of the challenge represented by the latter; finally, Section 6.4 analyzes some side issues regarding regulatory scenarios in different countries, with the related legal concerns.

6.1. Security and Privacy

The security and privacy of the data from individuals is a major concern. Considering the only recent emergence of (big) data analytics in healthcare, governance issues including security, privacy, and ownership have yet to be fully addressed [234, 94, 293, 143, 220].
Since cloud and fog-based solutions allow applications to process users data in third-party's hardware and software, their adoption introduces strong concerns about data privacy [287]. Issues often derive from the limited confidence in the provider in charge to store very sensitive data, in its infrastructure [242, 96], and from the related concern of loosing control over data [90]. Although the adoption of in-house hardware solutions in place of implementing outsourcing seemingly eases the management of big data with more information protection [65], external services are more and more adopted, as being able to guarantee required advanced security settings (e.g., adopting proper encryption algorithms, such those used by the financial sector [249]). In fact, high availability of the cloud-based services can only help the health organizations to provide uninterrupted services with minimum downtimes [6]. In the case of critical applications, multi-cloud solutions are often adopted to further improve availability for critical services [312, 118].
Indeed, literature makes evident how data sharing must be handled with innovative technologies and tools when it comes to cloud [6]. More specifically, the introduction of cloud computing poses a number of issues related to securing patients' data [6]: communication and data security and data privacy are the top priorities [6, 114, 42, 151, 22, 158, 166, 90, 27, 209, 240, 118, 314, 92, 296, 88, 183, 78, 186]. The same security concerns that apply to current virtualized environments can be foreseen to affect fog devices hosting applications. Isolation and sandboxing mechanisms must be in place to ensure bidirectional trust among cooperating parties [287]. Communication security [162, 324, 182], efficient data security mechanisms [182], data integrity and disaster recovery [6], as well as data privacy-related issues, such as the concerns related to privacy exposure, privilege abuse, or changing privacy landscape [107, 187, 2, 210] have also attracted the attention of the research community. When connecting (legacy) health information systems to the Internet, computer worms introduce additional issues to be addressed, and still represent a hot topic requiring research efforts for being detected as well as for characterizing their behavior and modeling their spread [71, 148].
A number of patient-specific privacy needs based on a wide range of factors, such as age, profession, and religion have to be taken into consideration [175]. Numerous ethical concerns have also been expressed in this area, such as those related to informed consent and the difficulty of providing meaningful access rights to individual data subjects who lack the necessary resources [206, 191]. To face them, new-generation consent forms have been proposed, specifically allowing patients to openly share

the data generated on them with researchers [65]. Additional security implications are also generated by IoT since the connected healthcare (wearable) devices can be at risk to hacking and hence require a secure uniqueness management and authentication to be implemented [8, 74, 188]. As everyday objects are potentially source of information security risks, the adoption of IoT in healthcare could significantly distribute those risks. Therefore, due to the resource limited devices usually adopted, it is an essential requirement to design lightweight algorithms in the secure data management system [319].

6.2. Design, performance, and efficiency

Dramatic changes in both big-data generation and acquisition create profound challenges for data management. Due to the massive amount of data generated by devices, defining the proper data archival, purging, and retention may result in a perplexing task [74, 215], to the extent that today it might now be less expensive to generate the data than it is to store, secure, and analyze it [65].

Meaningful, effective, and cost-effective mining and analysis of the input events prerequisite a robust analytics platform [74]. Since the lag between data collection and processing has to be addressed, real-time big-data analytics is another key requirement in healthcare. Evaluation criteria for big-data analytics platforms include availability, continuity, ease of use, scalability, ability to manipulate at different levels of granularity, privacy and security enablement, and quality assurance [234]. The dynamic availability of numerous analytics algorithms, models, and methods is also necessary for large-scale adoption [234, 143, 220].

Clever methods must be developed to replicate and store certain portions of the data both within organizations and at locations that maximize the performance of the overall analytic process [293]. Transferring data from one location to another represents a relevant challenge and can be even performed by shipping external hard disks containing the information [65]. Interesting alternative solutions consist in the use of different types of software to compress the data without losing pieces of information, or using peer-to-peer file-sharing technology to guarantee open-access sharing of scientific data [65].

Because of the relevant challenges in processing generated by data complexity, the variety of data is considered a major concern [293, 1]. The management of unstructured information poses additional challenges [65]. Moreover, processing enormous volumes of data published at a high rapidity needs a matching infrastructure. From the communications perspective, at the application level, innovative architectures should be implemented for the corresponding applications. Research-tailored specific cloud solutions for data storage and transfer also exist [102, 65, 326].

Cloud performance has diverse keys to the interpretation: while on the one hand cloud computing is a tool to provide metered services [55]—also thanks to the adoption of adequate monitoring strategies [4]—on the other hand, computing performance [283], efficiency of communication protocols [57], network performance (e.g., because of poor bandwidth and unpredictable latencies when transferring high volumes of traffic) [209, 90, 279, 281, 97, 210], still represent barriers. In accordance with the large adoption of solutions based on public clouds, research interest has recently focused also on the network performance of public-cloud, specifically on intra-datacenter networks connecting virtual machines within the same datacenter [224, 225], wide-area networks interconnecting public-cloud datacenters placed around the globe [228], as well as network paths connecting the cloud to final users [227, 15]. In more particulars, when dealing with data intensive applications, co-design approaches involving different stakeholders (particularly those in network/performance engineering roles) have to be taken into account to manage and troubleshoot service performance [15]. Specific platforms have been designed to orchestrate related measurement tasks [226].

However, cloud computing is still seen as a new technology for the involved entities not specialized in ICTs, and therefore technical and management issues have been also reported [166, 173, 61]. In addition, even though cloud technologies are known to be scalable, works in the literature report scalability of the implemented solutions to be a common concern [317, 91, 29].

Since most platforms to manage and process healthcare data currently available are *open source*, the typical advantages and limitations of open-source platforms apply. Therefore, the existing trade-off between lower development costs and the lack of technical support as well as minimal security must be addressed.

The IoT remains in its infancy in the healthcare field. Currently, for what specifically concerns the healthcare field, IoT research trends include

network architectures and platforms, new services and applications, QoS and scalability among others [136]. Because of the potentially drastic escalation of the connected devices, architectures are required to be more scalable [74, 170]. Communication frameworks are envisioned as the main enablers for distributed worldwide healthcare applications [40]. However, high network bandwidth is essential to read all the raw data generated by millions of associated devices [74].
The introduction of the fog paradigm carries additional open problems that will have to be addressed to make the fog a reality, especially when leveraged in the healthcare context. Computing nodes and applications running on top of the fog need to be properly configured. Having potentially billions of small devices to be configured (e.g., due to the possible integration with BANs), the fog heavily relies on scalable and decentralised management mechanisms, that need to be properly tested at this unprecedented scale [287]. Also, safety, reliability, availability, flexibility, maintainability, and power efficiency are commonly considered issues [95, 325].
Several design issues must be addressed in order to enable the deployment and adoption of BANs [56]. As BAN nodes require an energy source for data collection, processing and transmission, development of suitable power supplies becomes paramount [56]. Identifying proper data-compression approaches is often mandatory [267]. Energy harvesting is a possible solution to the problem taking advantage of body movements and temperature difference [56]. Therefore physical characteristics of sensor and actuator materials and electronic circuits are still considered open issues [44]. At hardware level, sensors—typically consisting of two parts, i.e., the physiological signal sensor and the radio platform—are needed to be lightweight, small-sized, non-invasive, wireless-enabled, and ultra-low-powered [56].
The radio part of the sensor consumes most of the energy and hence becomes one of most important entities to be considered. Therefore, further development and evaluation of improved propagation and channel models is needed [44], although in the past few years, researchers have made considerable progress in characterizing the body area propagation environment through both measurement-based and simulation-based studies. The MAC protocol plays a significant role in controlling the radio module and in reducing the average energy consumption of the sensor node.
Developing efficient routing protocols in WBANs is a nontrivial task because of the specific characteristics of the wireless environment. First of all, the available bandwidth is limited, shared, and can vary due to fading noise and interference, so the protocol overhead should be limited. Secondly, the nodes that form the network can be very heterogeneous in terms of available energy or computing power [177]. Improved networking and resource management schemes are considered as open issues [44].
In more general terms, with network densification and future deployment of IoT, wireless networks are expected to consume increasing amount of energy to meet desired performance in terms of both *quality of service* and *quality of experience*. Since energy is expensive for both users and operators and its production has an environmental impact, growing concerns over its conservation have been raised [263]. As a result, a number of research (e.g., in the are of *green communications* [292]) has been done in both industrial and academic sectors to investigate the energy consumption in the cellular networks and the key technologies to reduce its level [263, 255].

6.3. Heterogeneity and Interoperability

Healthcare systems are in rapid transition, moving from traditional, paper-based practices to computerized processes to deliver services. While healthcare organizations are developing systems supported by ICTs to better manage the quality and the service delivery, they are facing heavy challenges that have to do with the lack of interoperability among systems, generated by reduced ICTs skills as well as the complexity of the overall healthcare framework [305].
Heterogeneity and interoperability (of both data and technologies to be merged) are commonly considered obstacles and still represent open issues [6, 209, 252, 83, 96, 94, 65]. In more particular, biological and medical data are extremely heterogeneous (more heterogeneous than information from any other research field [65]). The diversity of the IoT objects exacerbates the heterogeneity problem of the data format in IoT-based platforms [315], to the extent that the absence of uniform standards for data generated from devices may prevent their widespread adoption [74, 274]. Indeed, the emergent market still does not make available flexible and easily adaptable products, suitable for being adopted in contexts other than those offered by the

manufacturer and that often allows only access to pre-configured servers in some cases [274]. In fact, the use of closed solutions may become a limitation when it comes to integrating IoT devices in a broader context.

Continuous data acquisition and data cleansing have to be addressed. Healthcare data is rarely standardized, often fragmented, or generated in legacy IT systems with incompatible formats [234]. Additional challenges arise from the gap that emerges between the low level sensor output and the high level user requirements of the domain experts [237]. For instance, EMRs are not designed to process high volume/velocity data or handle complex operations (e.g., anomaly detection, ML, pattern set recognition).

As the design and development of personal, ubiquitous, and pervasive healthcare applications often requires to integrate different kinds of sensor infrastructures, able to detect changes in patients' states and of sharing this information to interested caregivers, *context-aware middleware-level solutions* have been also proposed [30, 131, 23, 272, 243, 99, 264, 245, 239, 153, 142]. With the massive adoption of cloud, the adoption of cloud-based middleware solutions has remarkably increased [209].

6.4. Regulatory and legal issues

Along with the technological challenges the adoption of ICTs introduces, the legal and regulatory framework is a key area for policy-makers, healthcare providers, and the IT industry.

Indeed, the evolution of ICTs allows to more and more easily gather, transfer, store, and manage health-related data. Often, this data could be subjected to transfers across national, regional, or state borders, where little consensus exists about which authorities have jurisdiction over the data. Therefore, clients and providers will need to understand and comply with the different rules in place [251].

While privacy and security are important and well-known issues for healthcare organizations (as discussed in Section 6.1), differences exist in regulation policies between the US and across EU member states [69]: in the US, the Office for Civil Rights enforces the Health Information Portability and Accountability Act (HIPAA) Privacy Rule, which protects the privacy of individually identifiable health information [123]; in the EU, the Data Protection Directive (95/46) regulates the processing of personal data across the 27 member states [81].

While conventional healthcare is highly regulated, new ICTs-based healthcare paradigms are generally unregulated or under-regulated, raising questions about quality, safety, and data protection [277]. Due to its large spread and impact, to the best of our knowledge, only m-health is partially regulated. The US Food and Drug Administration (FDA) released a draft guidance regarding mobile medical apps in 2011 [31], while in 2015 it released its final guidance for industry and FDA staff on mobile medical applications [200], that should be considered by mobile medical apps developers [31]. In this document, the agency clarified that three distinct categories of mobile medical apps are considered: (i) apps that are medical devices subject to FDA oversight; (ii) apps that do not qualify as medical devices and therefore are not regulated by FDA; (iii) apps that are medical devices subject to FDA oversight, but for which the agency will refrain from regulating for the current time [31].

More in general, legal issues, related to data jurisdiction issues [173], to clinical and legal implications [166], or to service and data licensing [118, 96, 97] raise non trivial additional challenges.

7. Conclusion

Healthcare is a fundamental social and economic challenge, more and more exacerbated today by the increasing demand dictated by the aging and growing population. Fueled by technological advancements, ICTs play a primary role in this scenario where technology evolution keeps dramatically improving the positive impact they have on virtually the whole health domain, unveiling unprecedented opportunities and benefits.

In this survey we have analyzed more than 300 scientific papers, investigating how the health-domain landscape is being reshaped with the massive adoption of advanced ICTs, giving birth to both novel paradigms and application scenarios, as well as raising additional issues.

The main contributions of this survey are summarized in the following.

(I) We have identified and discussed a number of **ICTs-based healthcare paradigms**, that have better detailed the basic ideas related to the e-health concept first appeared in the 90s. Although some of them lack commonly-agreed definitions, the analysis of the literature about paradigms such as mobile, pervasive, ubiquitous, and personalized

health, has contributed to characterize the specific ways ICTs are able to underpin the applications that are deployed into the health domain today.
(II) The awareness about the centrality of healthcare-related data in today's applications deployment, has led us to review the highly-fragmented scenario originated by the scientific literature dealing with **health-data formats and their nomenclature**. We have identified and discussed the most popular ones (e.g., EMR, EHR, EPR, etc.), providing a unified view that integrates the existing literature.
(III) We have thoughtfully reviewed the impact of ICTs advances on healthcare, dissecting the scientific literature and discussing the **ICTs pillars** (e.g., networking technologies, mobile devices, WSNs, WBANs, AI, big-data analytics, etc.) **and paradigms** (e.g., cloud and fog computing, IoT, etc.) supporting healthcare applications. To the best of our knowledge, this is the first work to provide a holistic view of all these ICTs pillars in relation to health, whereas each survey only focused on one or two. In consideration of the ongoing spreading of the *Industry 4.0* paradigm, a holistic approach is the more and more critical to understand next future evolution, and we help fill this gap in literature. Our analysis has revealed that the fruitful coexistence and integration of these technologies is generating new opportunities by providing the foundation for introducing new applications as well as rejuvenating or even reinventing the classical ones.
(IV) The above considerations together with market-evolution trends have made healthcare one of the killer ICTs applications. This survey provides an **overall view of the most notable emerging applications**. These applications heavily enhance both effectiveness and efficiency of available healthcare solutions, dramatically improving cooperation among involved entities and cutting costs out. In more details, we have reviewed a number of different solutions proposed in the scientific literature (i) for health and wellness monitoring—ranging from disease monitoring to medication intake monitoring or assisted living; (ii) addressing genomic analysis; (iii) implementing cloud-bases information systems supporting healthcare; (iv) supporting personalized health and preventive medicine.
(V) We have discussed **recurring issues and challenges**, namely security, privacy, design, performance, efficiency, heterogeneity, interoperability, and legal issues. In fact, the adoption of ICTs in the health scenarios not only carries benefits and opportunities, but also amplifies well-known ICTs issues migrating them in the critical health domain.

These discussed contributions being given, this work is intended to provide a unified view and scientific survey of the impact of ICTs when applied to healthcare, thus helping the interested readership from both technological and medical fields not to lose orientation in the complex landscapes possibly generated when advanced ICTs are adopted in the critical application scenarios dictated by the healthcare domain.

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