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Innovative IT solutions in health and sport - the importance of wearable devices, Internet of Things, artificial intelligence and Big Data

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ABSTRACT

Abstract Healthcare faces a significant shortage of human and financial resources. One way to overcome this is to focus on preventive medicine, through the promotion of sport and the use of advanced IT (Information Technology) tools in healthcare. These tools include wearables, the IoT (Internet of Things), Big Data and AI (artificial intelligence). This narrative review article aims to present the current state of the art in the field to support the processing of literature at the beginning of new researches by reviewing the major literature focusing on three of the data management's functions: data collection, storing and processing. To quantify the studies, queries were run on ScienceDirect, PubMed, Web of Science, Google Scholar databases. The keywords used in the queries were "Internet of Things", "Big Data", "Artificial intelligence" and "Wearable devices" complemented by the terms "health" and "sports" so a total of 8 queries were run on each database. We selected only scientific articles which contain concrete results, present ICT tools used in health or sport, and were fully available from our institution's network so we examined 35 articles. The results of the queries show that in most cases more than 50% of the literature was published since 2019, so the topic is currently a highly researched area. On average, 59.57% of all published works were published from 2019 in Science Direct, 74.49% in PubMed and 77.18% in Web of Science. The above-mentioned IT tools on health and sport is significant. Their importance is most notable in the advancement of preventive medicine and innovation in medical research.

Kulcsszavak
Sport, egészségügyi informatika, Dolgok internete, viselhető eszközök, Big Data, mesterséges intelligencia

Absztrakt: Az egészségügy jelentős humán- és pénzügyi forráshiánnyal küzd. Ennek leküzdésére az egyik mód a megelőző orvoslásra való összpontosítás, a sport népszerűsítése és a fejlett informatikai eszközök alkalmazása az egészségügyi ellátásban. Ezen eszközök közé tartoznak a viselhető eszközök, az IoT („Internet of Things", Dolgok Internete), a Big Data és az AI (Artificial Intelligence, mesterséges intelligencia). Ennek a narratív áttekintő cikknek a célja, hogy bemutassa a terület jelenlegi állását, hogy támogassa a szakirodalom feldolgozását az új kutatások kezdetén, áttekintve a főbb szakirodalmakat, amelyek az adatkezelés három funkciójára összpontosítanak: az adatgyűjtésre, -tárolásra és -feldolgozásra. A tanulmányok számszerűsítéséhez lekérdezéseket futtattunk a ScienceDirect, PubMed, Web of Science, Google Scholar adatbázisokban. A lekérdezésekben használt kulcsszavak a következők voltak: „Internet of Things", „Big Data", „Artificial intelligence" és „Wearable devices", kiegészítve az „health" és „sports" kifejezésekkel, így összesen 8 lekérdezést futtattunk le minden adatbázisban. Csak olyan tudományos cikkeket választottunk ki, amelyek konkrét eredményeket tartalmaznak, az egészségügyben vagy a sportban használt IKT-eszközöket mutatnak be, és teljes mértékben elérhetőek voltak intézményünk hálózatáról, így 35 cikket vizsgáltunk meg. A lekérdezések eredményei azt mutatják, hogy a legtöbb esetben a szakirodalom több, mint 50%-a 2019 óta jelent meg, tehát a téma jelenleg erősen kutatott terület. A Science Directben átlagosan a publikált munkák 59,57%-a, a PubMedben 74,49%-a, a Web of Science-ben pedig 77,18%-a jelent meg 2019-től.

A fent említett informatikai eszközök az egészségügy és a sport területén jelentősek. Jelentőségük leginkább a megelőző orvostudomány és az orvosi kutatások innovációjának előmozdításában érhető tetten.

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Introduction

Today, the health sector is facing increasing challenges in ensuring its viability, both in terms of funding and human resources. Achieving one year of health gain is becoming increasingly costly, and there is a pressing need for a paradigm shift in medicine, as the efficient use of existing resources is an important issue (Sun et al. 2019). Classical medicine is reactive, with patients presenting to a doctor with pre-existing symptoms. However, the paradigm shift that is currently taking place will make medicine proactive, in which disease prevention and prediction, the anticipation of disease, will be a very important factor, saving considerable resources that could be spent on curing existing diseases (Shackleton and Gage 1995).

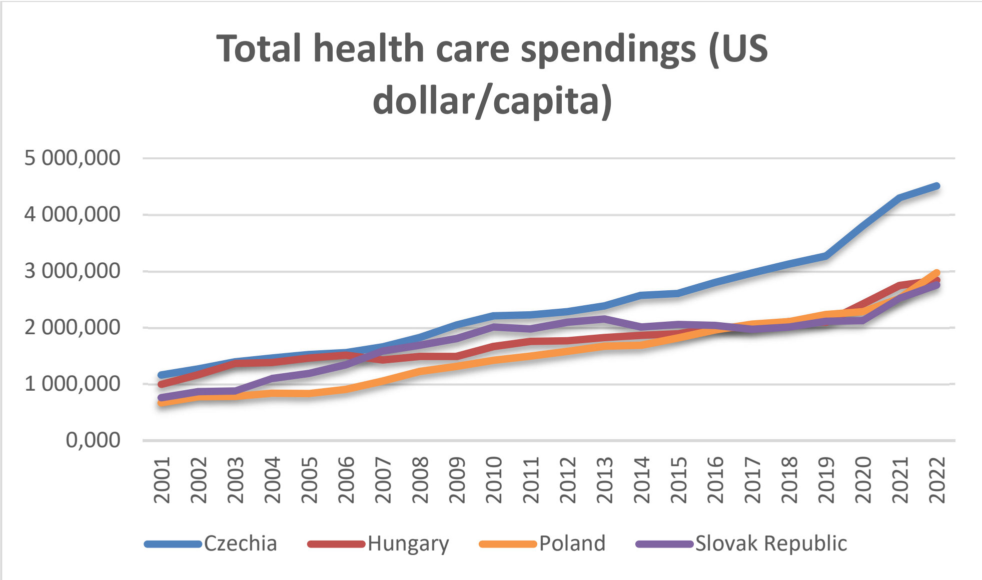
One of the most important tools for prevention is the development of sporting habits, which is influenced by many background factors (Charlton et al. 2014; Drake et al. 2015). In addition to stimulating sport, advanced information technology tools can be used to bring preventive medicine to the fore. The most advanced IT tools that can be used for this purpose are wearables, Internet of Things tools, Big Data and artificial intelligence. This article aims to present the state of the art in these disciplines.

Theoretical background

The Internet of Things (IoT) system is based on the advanced interconnection and co-operation of separate smart devices that can be used on their own (Hossain et al. 2018). During data collection, we collect an extraordinary amount of structured and unstructured data, which needs to be stored in huge databases, so it is necessary to clarify the concept of Big Data. Big Data is a large amount of data, but the term does not only refer to the amount of data, but also implies that this amount of data needs to be analysed using advanced methods in order to extract information and draw conclusions (Chang 2016). For such a large amount of data, artificial intelligence can be the answer as an appropriate analytical method. Artificial intelligence (AI) is the term used for computer systems developed to perform tasks that traditionally require human intelligence. These may include visual perception, speech recognition, decision-making or translation into a foreign language (Galimova et al. 2019). The importance of these technologies is significant in different sectors of the economy, but their impact in the health sector can be significant and has been recognised in many countries. The above-mentioned ICT (Information and Communication Technologies) devices can play an important role in both the treatment and prevention of diseases.

The management of chronic diseases places a very heavy burden on the economy. The cost of cardiovascular disease in the European Union is estimated at around €210 billion per year, according to European statistics (2017). Large labour shortages are also expected soon due to an ageing population (Wang et al. 2016). Health care expenditure is also steadily increasing, as shown in Figure 1. The data shows that the health care spendings in US dollars per capita has increased significantly in the Visegrad Group countries since 2001. One solution to reduce treatment costs could be to use previously unused treatment methods that introduce new methods including ICT devices at a lower cost than developing a new medical procedure. This could include the use of IoT, Big Data and AI devices mentioned above.

Figure 1.: Total health care spendings (US dollar/capita) (own ed.)



Source: own ed. based on OECD Data Explorer (https://data-explorer.oecd.org/)

In modern medicine, the emphasis is mostly on treatments. In ancient times, Greek, Chinese and Indian medicine proclaimed that the secret to longevity was in physical activity and a proper diet (Jákó 2012). The Lalonde Report, published in 1974, was the first to include a diagram of the „health field", which suggests that health is influenced by four factors: biological, lifestyle (including exercise habits), environmental and health care factors (Lampek 2015). However, this theory emphasises the importance of prevention. Improving disease management practices is therefore not enough to solve the health care's problem, as the solution for chronic diseases lies mainly in prevention.

Sport also plays a role in disease prevention. According to Nádori, sport is "physical activity that is practised according to specific rules, as a pastime or competitively. It has its origins in history and its present-day appearance as a solid social phenomenon, part of culture in all its forms." (Nádori 1976).

During sport-related investments planning it is essential to consider the factors that influence participation in sports. For instance, gender can impact sporting behavior, just as engaging in sports can affect traits like resilience (Blanco-Garcia et al. 2021). However, in analyzing the development of sporting behavior, it's important to emphasize the role of adolescent influences, including physical fitness, parental attitudes, gender, academic performance and socioeconomic background (Charlton et al. 2014; Drake et al. 2015; Herpainé Lakó 2021). Additionally, the significance of housing conditions and the type of settlement, which have been highlighted in various studies and may also affect motivation, should not be overlooked (Jiménez-Pavón et al. 2010; Guszkowska et al. 2016).

Hungarian studies have also shown that the type of place of residence plays a role in sporting habits. A larger proportion of rural respondents (31.5%) exercise at home compared to urban respondents (17%); 17.4% of urban respondents exercise in fitness and wellness centres compared to only 8.7% of rural respondents; 18.4% of urban young adults prefer club-based sports compared to only 15.2% of rural respondents (Kinczel et al. 2021). Physical activity also has an impact on overall health behaviour, with active lifestyles stimulating healthy eating (Veréb and Emri 2023). It also plays a role in maintaining physical and mental health and preventing the development of harmful addictions, thus influencing overall quality of life (Mikulán et al. 2010) and extends life expectancy (Tóth 2021).

Community support, involvement of sports clubs and easier access can significantly enhance sporting habits (Golle et al. 2014). However, the outbreak of SARS-CoV-2 (Severe Acute Respiratory Syndrome Coronavirus 2) in 2019 had a profound impact on community activities of this nature, potentially affecting sports participation, especially at the community or team level (Pfau and Kanyó 2023; Thompson 2022). One study found that distance learning during this period positively influenced individuals' attitudes toward sports (Barrett et al. 2021). Nevertheless, it is important to note that managing such initiatives would require substantial human resources. To address this challenge, Internet of Things (IoT) devices can be employed to enable remote monitoring in sports education (Gong et al. 2018; Yu 2018). In addition to IoT devices, it is important to highlight wearable devices as they are mobile devices that are usually with us, and thus can track our physical activity. The role of these devices is also important because they provide objective metrics to measure performance, as they can track a number of vital parameters such as heart rate, blood pressure, respiration rate, etc., and thus can be used to assess health status (Wan et al. 2018; Xiao et al. 2020). These feedbacks can also affect motivation (Juhász et al. 2020).

As we can see from the literature review, the role of ICT tools is very important in the field of health and sport behaviour development. However, due to the wide range of devices used, there is such a large amount of literature available on this topic that it is difficult to review and extract relevant information at the beginning of a research project. The aim of this article is to summarise the relevant literature, present the most commonly used tools in the research area and recent research through a narrative literature review to help starting new studies.

At the same time, the use of ICT tools to manage data which reflect health conditions implies the need to follow the legislation on the processing of personal data. Data management refers to the collection, storage, processing, use, transmission, disclosure, modification and protection of personal data (Bíró 2006). The literature review has divided data management by ICT tools into 3 main categories: data collection, data storage and data processing. This paper presents the articles processed for these three groups.

Material and method

There is a significant amount of literature on the subject in several scientific databases. To quantify the studies, we ran queries in ScienceDirect, PubMed, Web of Science, Google Scholar. These four databases were chosen because they are scientific databases that contain a significant number of peer-reviewed articles on the subject, many of which are available in full in English. Of all the results, we highlighted those published in the last 5 years, i.e. from 2019 onwards (Table 1).

In terms of keywords, we used terms covering the four major topics of our article - IoT, Big Data, Artificial Intelligence and Wearable Devices, - because these are the main types of ICT tools and methods used in the field - we complemented this with the terms health and sports so that we ran 8 queries per database. A list of the search expressions and boolean operators is also provided in Table 1.

Results

Looking at the data, we can see that a significant part of the literature for most search terms has been published in the last 5 years, excluding the Google Scholar database. These are also shown as a percentage of the total number of hits for the keywords. In red, we have highlighted those cases where at least 50% of the total hits appeared from 2019 onwards. For Science Direct, the percentages were lower for 3 terms, but still above 40%, and for the total search, the average number of hits for the last 5 years was 59.57%. For PubMed, all cases were above 50%. The average percentage was 74.49%, which is very high. For Web of Science, we also obtained a value above 50% in all cases, with an average of 77.18%. In Google Scholar, the values were well below those of the other databases, but it should be noted that this is the least accurate search engine of all those listed, as shown by the magnitude of the total number of hits.

Reviewing the search terms from 2019, different topics can be highlighted per database. In Science Direct, the most popular topics were Big Data healthcare and Artificial intelligence healthcare. In the PubMed database, the most prominent term was Artificial intelligence in healthcare, which had a multiple of the hits of the other keywords. Artificial intelligence healthcare and Internet of Things healthcare were the most popular terms in the Web of Science. In Google Scholar, Wearable device healthcare was the most popular topic for researchers. (Table 1).

We can see that the results of the search terms are very heterogeneous, but the term Artificial intelligence healthcare has given a high number of hits in the 4 databases we have studied. In any case, it is important to highlight the importance of this topic, which has many potentials and important research results to be expected.

We wanted to include scientific articles that deal with methods for collecting, storing and processing data on health and physical activity - the chapter on the Presentation of content follows this logic. For our narrative literature review, we have selected studies that are scientific articles, contain concrete results or present ICT technologies that are novel in their use in health or sport. We excluded from the review the articles that are not scientific articles (e.g.: proceeding papers, science promoting articles, book reviews, etc.), do not contain concrete results, do not present ICT tools used in health or sport, or presenting methods to improve health or sporting behaviour that do not use any of the four main methods we presented (IoT, wearables, Big Data, AI) or were not fully available from our institution's network. After screening, 35 articles were examined for content.

In the following, a review of the role of the four themes in health and sport is presented, with an overview of the main research results and innovative tools.

Table 1.: Survey results and their percentage distribution in the databases examined for the whole period and since 2019 (own ed.)

	Science Direct			PubMed			Web of Science			Google Scholar		
Search term	All results	Since 2019	Since 2019 %	All results	Since 2019	Since 2019 %	All results	Since 2019	Since 2019 %	All results	Since 2019	Since 2019 %
Internet of Things healthcare	23525	16581	70.48%	1570	1327	84.52%	7230	5764	79.72%	2130000	24600	1.15%
Internet of Things sport	11985	5186	43.27%	165	148	89.70%	578	464	80.28%	869000	18800	2.16%
Big data healthcare	63341	38655	61.03%	5799	3783	65.24%	5574	3741	67.12%	3990000	26200	0.66%
Big data sport	38670	15751	40.73%	758	580	76.52%	1275	869	68.16%	2400000	18300	0.76%
Artificial intelligence healthcare	31922	27359	85.71%	17938	13590	75.76%	7801	7388	94.71%	2760000	18600	0.67%
Artificial intelligence sport	10619	6259	58.94%	4119	2705	65.67%	971	836	86.10%	757000	18000	2.38%
Wearable devices healthcare	25111	17563	69.94%	4370	2574	58.90%	4613	3297	71.47%	490000	41500	8.47%
Wearable devices sport	16905	7854	46.46%	2356	1876	79.63%	1292	903	69.89%	97900	16800	17.16%
Average %			59.57%			74.49%			77.18%			4.18%

Source: own data collection from databases

Presentation of content

Wearable devices and Internet of Things

Portable devices in healthcare - Telemonitoring

Wearable devices are of paramount importance in remote monitoring, which involves monitoring the user's vital signs outside healthcare facilities. Data collection can be periodic or continuous (Kő and Szabó 2015). The way in which data are collected depends on the purpose for which they are used. Typically, data collection applications can be installed on smartphones, used with smartwatches, smart bracelets, or combined with smart devices in the home (Internet of Things, IoT) and connected to the data collection centre via various wireless networks. The system can then analyse the data and make recommendations to the patient or the doctor, so that the patient can receive personalised treatment at their next visit. Of particular importance is that in certain emergency situations, in case of sickness, it can also help to detect the pathological condition in time, assist the on-site care team and help the patient. The use of such an application is of particular importance in view of the increasing number of patients with cardiovascular disorders and the longer response times for ambulances (Yang et al. 2013).

Wearable devices in sport

Smart devices can improve lifestyle by stimulating continuous physical activity. However, in addition to smartwatches and smart bracelets, other devices are available to measure other variables beyond those normally measured by smartwatches, thus complementing physical activity monitoring. In a study on three subjects, the use of a smartwatch in combination with a smart scale increased maximum BPM (beats per minute), thereby increasing adaptability to exercise and reducing body weight, thus improving subjects' body mass index. A disadvantage of this study is that it was conducted in a small number of subjects, so its results should be treated with caution (Chong et al. 2021). Another valuable parameter may be the measurement of blood oxygen levels. A research has shown that wearable devices can also be an excellent way of measuring this. After analysis, the data obtained from these can be used to reflect a healthy lifestyle and to assess changes in aerobic system dynamics, such as cardiorespiratory fitness and the index of general health (Beltrame et al. 2018).

A wireless blood pressure monitor can also be added to the smartwatch, for example. Such a study was initiated by Golbus and colleagues and was divided into two phases: a 45-day intensive collection phase (Phase 1); and a 3-year longitudinal follow-up phase (Phase 2). Based on data from the first 45 days of Phase 1 and Phase 2, they found that blood pressure and resting heart rate varied by sex, age, race and ethnicity, with men having higher blood pressure and participants aged 65 years and older having lower heart rates. The number of steps per day and distance walked were lower in women and those aged 65 years and over. Socio-demographic factors should therefore be taken into account when planning such interventions (Golbus et al. 2021).

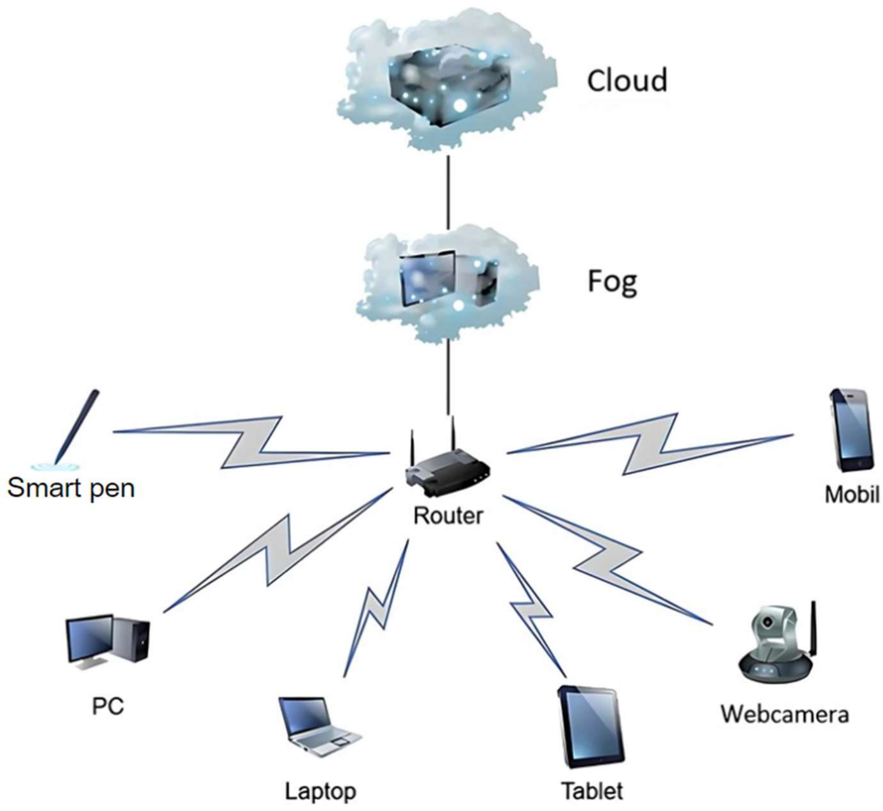
Types of data collectors, data processing

According to a 2016 US study, data collection devices can be classified into three categories: implantable, wearable and external mobile devices that collect data on patients' health in real time and store it on a cloud-based system. This approach allows for the storage of large amounts of data and easy access to data, making it easy to automate data analysis (Shinbane and Saxon 2016).

According to the paper documenting the research, in order for this automation to take place, a purpose-built digital infrastructure with artificial intelligence as a key component needs to be put in place. The system will process the data as it is collected and report only those cases that deviate from the normal values. Examples include a spike in heart rate or much higher than normal blood pressure. It allows to study cases that could not have been observed before, as a wide range of patients can be observed regardless of their geographical location, and more accurate information can be obtained by continuous data collection. Such systems still require much analysis, appropriate infrastructure and patient-patient interaction to be effective, to improve quality of care, costs, accuracy of diagnosis and overall patient perception, and potentially to create a global health system (Shinbane and Saxon 2016).

Fog computing is also used in the application of IoT devices, which refers to the processing of data at the logical layer between cloud-based data storage and IoT devices (Figure 2).

Figure 2: Location of fog in the IoT



Source: own ed.

The importance of this was highlighted by Mutlag et al. in their work summarising 99 peer-reviewed papers. According to the literature reviewed in their survey, the importance of Fog computing is important in real-time, low-latency, high-response-time domains, such as healthcare. Resource sharing is one of the most important elements of fog computing, providing, among other things, low latency, higher security and better error tolerance. The research reviewed focuses on very different areas, showing that the field is still very untapped, but the potential is remarkable (Mutlag et al. 2019).

Healthcare and technology have always been intertwined, but this relationship has changed significantly in recent years due to the rapid development of IoT and the popularity of wearable devices. This has led to personalised healthcare, improved access to healthcare and a level of customisation never seen before. These advances, while exciting, must be accepted with care, as there remain legitimate concerns about consistency, safety, cost-effectiveness and other critical factors. Many changes are needed to make this technology viable in the medical field. Most importantly, the hardware and software must be designed to work well with the new "Internet of Things" technologies to address their role in healthcare. The aforementioned article examined many important aspects of IoT e-health technology, including wearable health sensors, body surface sensors, advanced comprehensive health systems and Big Data analytics, which are of paramount importance for the delivery of e-health services (Firouzi 2018).

As data collectors continuously collect data, they create a huge amount of data, which can be structured or unstructured. This dataset is collectively referred to in the literature as Big Data (Manogaran et al. 2018). We will discuss Big Data in more detail in the next chapter.

Electronic Health Record (EHR) and its benefits

One method of storing health data is the electronic health record (EHR), which is a digital format for storing information about a patient's health status (Sahney and Sharma 2018). Another way of describing an EHR is that it is a 'long-term health record', which includes all the information about a patient in the health record, such as the patient's health profile, behavioural and environmental information (Amatayakul 2007).

The EHR also contains demographic or personal information in addition to health data, such as age, weight, billing information, and vital signs, past and present medical history, family medical history, medication and allergy history, immunization information, laboratory test results, and radiology images, and can be shared among providers. According to Sahney and Sharma, digital health records reduce the risk of data replication because files can be shared between different health systems, modified and updated, which reduces the risk of lost paperwork. EHR systems can be useful in extracting medical data from large population studies, which can also predict long-term trends in patient condition changes, and help improve patient health through better disease management.

The article identified five important aspects in which EHR systems are significantly preferable to paper-based health records, as follows (Sahney and Sharma 2018):

- cost,
- storage,
- security,

- access
- legibility and accuracy.

Critical factors in EHR implementation

However, there are a number of key factors to consider when implementing EHR systems. Gesulga and colleagues have conducted a detailed review of the literature analysing the barriers to EHR system implementation. Their summary provides insights into how barriers to EHR implementation relate to information systems resources. User resistance, lack of education and training, and data security concerns were the main barriers identified by the literature articles analysed. It is also important to examine how individual health care institutions are addressing these problems (Gesulga et al. 2017). EHR capacities need to be maximised to improve the quality, safety, efficiency and effectiveness of health care systems (Sahney and Sharma 2018).

Big Data

As mentioned above, Big Data involves not only huge amounts of data, but also the processing of that data. The importance of the subject is demonstrated by the fact that the President of the United States of America has approved an investment of around USD 200 million for research into Big Data (Chang 2016).

Dimensions of Big Data

According to several approaches, Big Data is characterised by 5 important dimensions, each of which is named with the letter "v", and can therefore be referred to as the 5 "V "s. The first dimension is volume, which is also the name of the concept. The second dimension is variety, which can easily exist with large amounts of data, with many combinations of structured and unstructured data types. One of the reasons for this is that data come from multiple sources and in multiple forms. The third dimension is velocity, which, by definition, refers to the speed with which data can be processed. For large datasets, the speed of performing operations and analyses is crucial, otherwise the result will no longer be relevant after a long waiting time, especially when dealing with rapidly changing data, such as health data.

The fourth dimension is veracity. As we will draw conclusions from the results, it is an essential property, as wrong conclusions can be drawn from wrong results and these can form the basis for wrong decisions. The fifth dimension is value, which is the value of this data set to the institution or user using it. This depends, of course, on the nature and function of the institution or company processing the data (Chang 2016; Palanisamy and Thirunavukarasu 2017).

It is important to note that very different analytical applications can be used. Therefore, it can be an extremely big mistake to rush into purchasing expensive Big Data tools without thinking it through, and organisations should first understand the mechanics of each Big Data analytics system before making a purchase (Sivarajah et al. 2017). In the near future, other new features, best practices, benefits and outcomes of this technology may become even more prominent. In the light of these future opportunities, the potential of Big Data research with a strategic focus could help to increase the number of technological and management-oriented research projects (Wang et al. 2018b).

Linked data

Big Data is characterised by the diversity and unstructured nature of data types, as discussed above. In this context, it is worth mentioning the concept of linked data, also known as open data, which are structured, mostly publicly accessible data sets. Although there is much disagreement among publishing experts on the concept of Big Data, there is agreement that linked data falls into this category. The relevance of Big Data in research is that it provides an excellent environment for testing different data processing methods, as it is composed of automatically interpretable linked data that can be combined with each other. Whether structured or unstructured data, similar methods are needed to organise, maintain, manage, explore and use them (Drótos 2014).

Big Data in healthcare

In terms of Big Data, there is also a lot of research in the healthcare sector to ensure that the increasing amount of data generated in the sector is not only stored for archiving purposes, but that the information is extracted from it in the most useful way. According to Krittanawong's article, in everyday clinical practice, physicians are under more pressure than ever to innovate due to the rapid, exponential growth of health data (Krittanawong 2018). In fact, Big Data itself, in its raw form, is meaningless, but its processing can, among other things, accelerate breakthroughs in medicine - which in turn can change current clinical practice. Doctors can analyse huge data sets, but this currently requires a lot of time and sophisticated analytical tools such as supercomputers. The rise of artificial intelligence in the era of Big Data, however, can help doctors shorten processing times and improve the quality of patient care in clinical practice (Krittanawong 2018).

Wang and colleagues (2018a) were able to identify five big data analytics capabilities based on content analysis of 26 Big Data-based cases in healthcare, which were:

- ability to analyze nursing patterns,
- ability to analyze unstructured data,
- decision support capability,
- inference ability,
- traceability.

Analytical capability refers to the techniques commonly employed in Big Data analytics systems to process vast amounts of highly variable data at high speeds, utilizing specialized technologies for data storage, management, analysis, and visualization. In healthcare, analytical capabilities can be harnessed to identify patterns of care and uncover associations within extensive health records, providing a comprehensive view of evidence-based clinical practices. Health analytics systems address the increasing demand from healthcare organizations to process large data volumes in parallel, manage real-time or near-real-time data, and capture visual data from patients or their medical records.

The primary distinction between the analytical capabilities of Big Data analytics and traditional data management systems lies in the former's unique ability to analyze semi-structured or unstructured data. In healthcare, unstructured and semi-structured data encompass information that cannot be stored in traditional relational databases or conform to predefined data models. Examples include XML-based electronic health records (EHRs), clinical images, administrative records, and laboratory results.

Decision support capability is designed to assist managers in making informed decisions and taking appropriate actions. This capability typically generates shareable information and knowledge, such as patient histories, summaries, detailed queries, statistical analyses, and time series comparisons. Such information is invaluable for implementing evidence-based medicine, identifying advanced disease surveillance alerts, and enhancing personalized patient care. Inference refers to the ability to build and evaluate models that produce accurate predictions for new observations, utilizing sophisticated statistical tools and models that provide insights into future conditions. Traceability involves tracking data across all information technology components within an organization's service units. Healthcare-related data - such as activity and cost-based data, clinical data, pharmaceutical research and development data, and even patient behavior data - are often collected in real-time or near real-time from healthcare providers, pharmaceutical companies, consumers, and stakeholders outside the healthcare sector (Wang et al. 2018a).

However, there are still significant challenges in the health sector, where complex data often needs to be managed and data protection issues can be much more prominent than in other areas. Nevertheless, it seems clear that the above approaches can be used for a wide range of purposes, such as stratification of patients, improvement of triage systems and prediction of decompensation. To make this possible, governments need to develop policies that allow the collection of and access to large data sets, as only as a result can accurate and high-quality predictions be made and benefits realised (Bates et al. 2018).

Big Data in sports

Sports big data come from the Internet and show a rapid growth trend. Sports big data contain rich information such as athletes, coaches, athletics, and swimming. Big Data applications in sports mainly focus on evaluation and forecasting. Their prominent methods include predicting athlete performance in knowledge graphs, finding rising stars in sports, creating a unified sports big data platform, providing open sports big data, and protecting privacy (Bai and Bai 2021). In sports management, big data is used on and off the field to guide decision-making across the sector (Watanabe et al. 2021).

Critics of Big Data

As with all scientific methods, it is important to analyse the results of Big Data critically, taking into account the negative factors. One of the strongest critics of Big Data, Jordan, points out the following in his article published in 2015. It is a serious, thoughtful task to ensure that we can use the technology to get the right data to the right person at the right time. For patient records, this could mean:

1. Relevant data

It is not only the veracity of the data that is worth questioning, but also the applicability of the data and, perhaps most importantly, the availability of the data.

- If a specific record contains data from, for example, fitness apps, how can we verify that the data was actually generated by the patient?
- Are the records kept from electronic health records up to date?
- Do we have appropriate access to the data? We may have advanced EMR (electronic medical record) datasets, but do we also have agreements with popular fitness providers or patient-centric data collectors?

2. The right person

When we think about the right person, we should not only think about the analysts themselves, but also consider the technology that the analyst may use.

- How well are the physicians involved in the processing able to see through the data sources in the registry?
- Do we have technology that can ask questions in the right way, can interrogate the data and in doing so can use the whole medical record?

3. The right time

When using Big Data technology, we have to face the fact that the underlying data can change in a very short time.

- Can we reach individual patients in the time interval when their physical condition, adherence to therapy and the data in their current medical records are appropriate for our research?
- Have there been any life events that have negatively affected the patient's adherence to therapy, even years ago?
- Has the patient's medical history been checked against the inclusion/exclusion criteria of the clinical trial (Jordan 2015)?

Artificial intelligence

The importance related to Big Data lies in the fact that it can easily automate the processing of structured and unstructured data, which is essential when using Big Data.

Shapiro defined artificial intelligence (AI) in the early 1990s as the branch of science and engineering focused on understanding computational aspects of intelligent behavior and creating systems that exhibit such behavior (Shapiro 1992). AI systems are essentially programs that enable computers to operate in ways that give the impression of intelligence. The British mathematician Alan Turing, one of the pioneers in modern computer science and AI, explored the concept of intelligent behavior in computers, particularly their ability to perform cognitive tasks at a human level. This line of inquiry eventually led to what is now widely known as the "Turing test."

Artificial intelligence and learning

Machine learning, a prominent area within AI, encompasses a range of techniques designed to tackle the intricate challenges of Big Data by uncovering patterns in the interactions between variables. Unlike traditional statistical methods, machine learning emphasizes the development of automated clinical decision systems, such as those for predicting readmission and mortality, which assist physicians in making more accurate forecasts beyond basic statistical projections.

Krittanawong and colleagues categorize machine learning into three types: reinforcement, supervised and unsupervised learning. In supervised learning, algorithms rely on a dataset labeled by humans to predict a specific, known outcome. This approach is particularly effective for classification and regression tasks, but it demands extensive data and is labor-intensive, as the labeling process must be done manually. On the other hand, unsupervised learning is used to uncover new disease mechanisms, genotypes, and phenotypes by identifying patterns within the data without human labels. The goal here is to detect hidden structures in the data. For instance, training medical residents before they see patients can be likened to supervised learning, where labels are provided. Conversely, allowing doctors to examine patients without prior labeling, learn from their mistakes, and devise their own treatment plans corresponds to unsupervised learning. Certain algorithms, like Artificial Neural Networks (ANNs), can be trained using either supervised or unsupervised methods to enhance the accuracy of automated predictions. Lastly, reinforcement learning serves as a blend of supervised and unsupervised learning. It seeks to improve algorithm accuracy by leveraging and interpreting trial-and-error processes (Krittanawong 2017).

The role of artificial intelligence in the medical sciences

The application of AI technology in surgery was first explored by Gunn in 1976, when he explored the possibility of diagnosing acute abdominal pain using computer analysis (Gunn 1976). The development of medical AI has been coupled with the development of AI programs to assist the physician in making diagnoses, therapeutic decisions and predicting outcomes. One of the roles of AI is to support healthcare workers in their daily tasks by assisting them in performing tasks based on manipulation of data and knowledge. Such systems include artificial neural networks, fuzzy expert systems, evolutionary computation and hybrid intelligent systems (Ramesh et al. 2004).

The use of artificial intelligence techniques in health research has increased dramatically in recent years. The ability to generate and store datasets of unprecedented size and the speed of computation has enabled an explosion in the development of artificial intelligence. It was the image-based diagnostic area of healthcare that was directly transformed by AI, think of the possibilities in dermatology, radiology or pathology. In their pioneering study, Esteva and colleagues used Google's Inception convolutional neural network architecture to classify melanoma and non-melanoma features in images of skin lesions. Their results showed a picture broadly in line with the consensus of experts (Esteva et al. 2017). In another study, Campanella and colleagues exploited the potential of AI by diagnosing images of biopsies that were likely to have prostate cancer features (Campanella et al. 2018). And Bejnordi and colleagues have used AI to classify histological material with high accuracy in terms of whether it showed features of benign or malignant breast cancer (Bejnordi et al. 2017).

A key factor contributing to the success of AI-driven diagnostics is the incorporation of a wide array of algorithms into the training process. Another significant source of big data is the electronic health record, which holds immense potential for AI-based analysis. This record provides a unique opportunity to leverage comprehensive patient data, encompassing details about treatments, diagnoses, relapses, and co-morbidities. It's no surprise that AI researchers have utilized this data to develop predictive models - employing both linear models and neural networks - to address various patient care challenges, such as predicting readmissions or assessing the risk of specific medical events (Gilvary et al. 2019).

Manogaran and his team have achieved notable progress at the intersection of artificial intelligence and medicine by employing the previously mentioned IoT tools. Their paper introduces a GC (Grouping and Choosing) architecture, named MF-R (Meta Fog-redirection), designed for continuous patient health monitoring. This architecture is composed of three phases: data transmission, data collection and Big Data storage. During the data collection phase, IoT sensors monitor the patient's health by measuring indicators such as heart rate, respiratory rate, body temperature, blood pressure and blood glucose levels. The gathered data is stored on Amazon S3 cloud storage. To safeguard this data in the cloud, the GC architecture, along with a key management scheme, is implemented to prevent unauthorized access. The GC architecture categorizes data into critical, sensitive and normal, thereby providing tailored security services. Once the data is stored in the cloud, the IoT-based health monitoring system applies the SGD (Stochastic Gradient Descent) algorithm with logistic regression to predict heart disease. Historical clinical data, sourced from the Cleveland Heart Disease Database (CHDD), was also utilized to "train" the prediction model. The effectiveness of this health prediction system was evaluated using several metrics, including Specificity, Sensitivity, Recall, Precision and F-Measure. Additionally, CPU demand and arrival time were considered as critical parameters for assessing the efficiency of the monitoring system (Manogaran et al. 2018).

Krittanawong and colleagues (2017) achieved the aforementioned results in their research on cardiovascular (CV) disease. They believe that deep learning's application in Big Data analytics holds significant promise for uncovering new genotypes and phenotypes associated with various CV diseases, including HFpEF (heart failure with preserved ejection fraction), Brugada syndrome, hypertrophic cardiomyopathy, Takotsubo cardiomyopathy, primary pulmonary hypertension (PH), hypertension (HTN), metabolic syndrome and atrial fibrillation. The advancement of artificial intelligence and precision medicine is poised to enhance the treatment of cardiovascular conditions.

In the future, cognitive computing systems like IBM Watson could become standard tools in healthcare settings, assisting doctors in making informed decisions and predicting disease outcomes. While AI will not replace doctors, it is crucial for physicians to understand how to effectively utilize AI to formulate hypotheses, conduct Big Data analysis, and optimize AI's application in clinical practice, paving the way for an era of precision CV medicine. However, overlooking the challenges associated with AI could skew its impact on CV care (Krittanawong et al. 2017).

Artificial intelligence in sport

Recent studies are increasingly focusing on the application of AI in analyzing basketball team and player performance, predicting tournament outcomes, shot analysis and prediction, AI-based training systems, intelligent training machines and arenas, and sports injury prevention. The majority of research indicates that AI technology can enhance the training quality of basketball players, assist coaches in devising effective game strategies, prevent sports injuries, and increase the enjoyment of the game (Li and Xu 2021; Beal et al. 2019). Moreover, recent advancements in applying artificial intelligence to orthopedic surgery and sports medicine have shown significant potential in predicting injury risks for athletes, interpreting advanced imaging, evaluating patient-reported outcomes, reporting value-based metrics, and enhancing patient experiences (Ramkumar et al. 2022).

Researches using artificial intelligence

In recent years, the identity of medicine as a data-rich, quantitative discipline has been significantly reinforced, particularly through the widespread adoption of electronic data collection and management systems in both clinical practice and biomedical research. This abundance of data is driving the transformation of medicine into a robust, numerically based science, while also opening up new avenues for conducting biomedical research. Data-driven studies are becoming increasingly prevalent, focusing on uncovering new and often unexpected insights. Imaging and molecular diagnostics have become standard tools for the precise assessment of diseases, and the expansion of guidelines and protocols has helped to standardize patient care.

Effectively harnessing knowledge is also crucial in developing decision-making tools and extracting meaningful information from data. In this context, the field of intelligent data analysis is particularly relevant. Given the broad applications of AI in medicine - from molecular medicine to organizational modeling - it is advisable to reassess the role of human reasoning and cognitive science in these areas (Patel et al. 2009).

Summary

Currently, medicine is facing a severe shortage of human and financial resources. Treating chronic diseases and research into new treatments is increasingly expensive. To address this, treating diseases with different, cheaper treatments using ICT tools and preventive medicine has become a priority, which can be achieved by promoting sport and using advanced IT tools such as wearables, Internet of Things (IoT), Big Data and artificial intelligence. The paper presented the current state of the art in the field by analysing the major literature works following the logic of data management (data collection, data storage, data processing). For the research, queries were run on ScienceDirect, PubMed, Web of Science and Google Scholar databases using the keywords "Internet of Things", "Big Data", "Artificial intelligence" and "Wearable devices", supplemented by the terms "healthcare" and "sports". The results show that most studies were published from 2019 onwards, indicating that this topic is currently an active area of research. The percentage of new works published since 2019 is over 50% in all databases except Google Scholar, and 4.18% in Google Scholar, but the accuracy of this search engine may be lower. Research shows that these IT tools have a major impact on health and sport, playing a prominent role in preventive medicine and innovation in medical research.

Limitations

From the literature review carried out, we can see that the importance of ICT tools in health care treatments, studies and prevention is highlighted, with a significant amount of recent literature available in the field. However, it should be highlighted that when using ICT tools in this way, it should be borne also in mind that user resistance, lack of training and data security may be problems, which need to be taken into account and to which institutions using these methods should pay particular attention.

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