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Application of Industry 4.0 Concept to Health Care

Lenka LHOTSKA[a,b1]
[a] Czech Institute of Informatics, Robotics and Cybernetics
[b] Faculty of Biomedical Engineering, Czech Technical University in Prague, Prague, Czech Republic

Abstract. The paper describes the concept of the Industry 4.0 and its reflection in health care. Industry 4.0 connects intelligent production concepts with external factors, including those linked with the production and those linked more with human, as for example intelligent homes or social web systems. Communication, data and information play an important role in the whole system. After explaining basic characteristics of the Industry 4.0 concept and its main parts, we show how they can be utilized in the health care sector and what their advantages are. Key technologies and techniques include Internet of Things, big data, artificial intelligence, data integration, robotization, virtual reality, and 3D printing. Finally, we identify the main challenges and research directions. Among the most important ones are interoperability, standardization, reliability, security and privacy, ethical and legal issues.

Keywords. Industry 4.0, Health 4.0, artificial intelligence, Internet of Things, Virtual Reality, monitoring

Introduction

The technological development brings new challenges and radical changes to many areas. Health care industry is definitely one of them. The changes are materialized by current digital transformation. The first changes were observed few decades ago when direct transfer of measured data, signals and acquired images from medical devices to computers started. Afterwards information systems, decision support systems, image and signal processing tools were introduced. Recent development in wireless technologies, sensors and Internet of Things (IoT) enhance possibilities of continuous data acquisition. Roles of the patient and the care system as such are changing. Patient shifts more to the role of a consumer and care becomes more patient/consumer centered. All these changes will finally generate a new ecosystem where data play an important role and help better understand the health consumer needs and better tailor a cost-efficient health offering to deliver care at the right time and the right place. These changes are closely linked to the emerging concept of P4 health care – Participatory, Predictive, Preventive, Personalized.

In the health care domain, we could see the terms Health 2.0 and Health 3.0 in last two decades and recently Health 4.0. Health 2.0 was introduced in the mid-2000s, as the

[1] Corresponding Author. Lenka Lhotská, PhD, Czech Institute of Informatics, Robotics and Cybernetics and Faculty of Biomedical Engineering, Czech Technical University in Prague, Prague, Czechia; Email: Lenka.Lhotska@cvut.cz

subset of health care technologies mirroring the wider Web 2.0 movement. Health 3.0 is health related extension of the concept of Web 3.0, utilizing user preferences and semantic web concept. Finally, Health 4.0 reflects the development in the industry where the concept Industry 4.0 was introduced in 2011 [1, 2]. The aim of the paper is to describe the main ideas of the Industry 4.0 concept and to point out their reflection in the health care. In other words, what can we learn from the application of Industry 4.0 concepts in the industry? How can the concept and lessons learned be applied to health care?

1. Industry 4.0

The Industry 4.0 concept is based on distributed control and decision making, into which various systems are integrated. It is reflected in the concept of intelligent production that is not closed in a particular factory environment. It also considers external factors, such as logistics, energy, and requirements, plans or orders from the customers. Further it is connected with mobility, intelligent homes and buildings, social web systems, etc. It is also called Internet of things, services and people. Important role in this ecosystem is played by data and information acquired from the data. Intelligent production builds on mutual communication of individual components that is no more centralized and are partially autonomous units. The processes of optimization and automatic planning and scheduling of production become more important. Another important item is knowledge of model of individual parts of the whole system. This knowledge is important at diagnostics and predictive maintenance. Greater portfolio of various sensors, and thus measured physical quantities, supply high volume of information, impossible to acquire in the past. The data and information support acquisition of knowledge about product utilization and influence the product properties.

In addition to machine-machine interaction, human-machine interaction is becoming more frequent and important. It includes production control processes, direct production and human-machine collaboration. Participation in direct production requires safe form of human collaboration with machines, mostly robots. Collaborative activities between human and robot require completely different paradigm of robot control that allows not only sufficiently fast activity to be performed, but also not to endanger surrounding environment, in particular human.

The core of the concept is connection of virtual cybernetic world with the world of physical reality. It brings significant interactions of these systems with the whole society, thus with the social world. From the point of view of modern system theory, we can call this development cyber-physical-social revolution, causing dynamic interaction of complex cyber-virtual systems, systems of physical world and social systems. The technological assumptions are based on information and cybernetic technologies, big data, autonomous robots, sensors, cloud computing and data storage, additive manufacturing, augmented reality, internet of things, and last but not least the whole scientific discipline of cybernetics and artificial intelligence that constitutes the core (both in ideas and technology) of the current “industrial revolution”. The listed topics are accompanied by such issues as data privacy and security, system security of critical infrastructures and energy systems, privacy protection, intellectual property protection. Standardization and legal adjustments are inevitable parts of the whole process.

1.1. Characteristics of Industry 4.0 Concept

Industry 4.0 transforms production from independent automatized units to fully integrated, automatized and continuously optimized production environment. New global networks based on interconnection of production equipment into cyber-physical systems will emerge. The basis of production transformation of high quality is a thorough analysis of all data sources that come into play in a given production environment. This applies both to the current situation and to the intended future solution. The infrastructure and tools for data collection and related storage and analysis systems must meet the requirements so that changes or extensions of production processes do not result in a complete change of the digital layer. In most of the applications, we assume the collection and evaluation of data (or at least selected groups of data) in real time. This data forms the basis for meeting most of the requirements of digital transformation (production planning and control, monitoring the status of machines, orders and performance of operators, implementation and use of digital twins, use of IoT, robotics, working with big data, use of artificial intelligence algorithms, cyber security). The following requirements must be met for such functionality [3]:

- Acquisition, transformation and storage of data for subsequent analysis in near real time, i.e. with minimal latency;
- Continuous and uninterrupted flow of relevant data from primary information systems to the analytical data repository (data warehouse);
- Permanent and uninterrupted "functioning" of the central data storage, when, in contrast to batch data upload, the functionality of the analytical solution is not possible to fail;
- Synchronization of data entities across all customer systems, i.e. the ability to obtain, for example, a complex customer object from several primary systems with minimal latency;
- Ensuring the quality of data, i.e. their cleaning so that the data enters the central repository for analytical processing in the highest possible quality;
- Minimum requirements for primary systems, i.e. ensuring minimum consumption of system resources of primary systems when extracting data from them;
- Scalability of the solution must ensure the ability to process so-called mixed workloads, i.e. processing of very different volumes of data - data integration solution for real-time analysis of production data must be able to process a continuous flow of smaller volumes of data, but must also be able to work with batch processing of large data volume in a short time;
- Part of the data integration process is usually the storage of transformed data in a central data warehouse, the data warehouse architecture must be prepared for the need for real-time analysis, historical analysis or analysis of historical and current data at the same time, i.e. for data integration of various nature within the data storage.

1.2. Selected Items of Industry 4.0 Concept

The text is inspired by the book [3] that provided deep analysis of current situation and future visions of Industry 4.0 and its impact on the Czech Republic.

1.2.1. Data Integration

Data integration serves for several purposes, the most important ones are production planning, management, monitoring the state of machines, orders, and performance of operators.

Production planning and management is always closely related to the character of production (mass production on one side and production of unique pieces on the other side). Currently, mostly a planning system is used within the CAD system for production design and layout in terms of the use of input material. In connection with the expansion of automation and robotization of production and handling between individual production operations. It will be desirable to implement a planning and scheduling system to control the entire production process to optimize the entire production process from order acceptance, material preparation for machines to storage of finished products and subsequent dispatch for customers. The classic planning is also approached by scheduling follow-up operations so that all devices are used to the maximum and there are no unnecessary pauses caused by waiting for the previous operation to complete. Planning and scheduling are closely related to the use of artificial intelligence algorithms, especially optimization algorithms.

Monitoring the state of machines, orders and performance of operators assumes the collection of data from machines and sensors suitably located in the production area. Most newly manufactured machines and equipment already have integrated sensors that allow to collect basic data about the operation of the machine. This data is sent to the computer system and is used for analysis from the point of view of predictive maintenance. This means that using artificial intelligence algorithms, it is possible to better plan machine downtime and perform maintenance before a failure could occur, which in most cases means a longer shutdown of the machine. There may be several approaches depending on whether the machine can be replaced by another machine during the shutdown with the need to change the production schedule, or whether the machine cannot be replaced. The downtime can then significantly disrupt the production plan and schedule. That is why predictive maintenance has such a big impact on production operations.

The collection of production data in combination with information on incoming and initiated orders allows more accurate monitoring of how individual orders are processed, and thus inform the customer about the time of processing his/her order. This feature is widespread in e-shops today, but is not yet possible in a similar time horizon for production processes that have a specific character.

Monitoring operator performance has several aspects: accuracy and precision of production, adherence to defined procedures and work safety. The first two aspects are closely linked to the previous points (data collection from machines and sensors and ordering information). The last one directly concerns the operator (e.g. sudden change of health condition, injury). Stored data can help in subsequent analysis to identify the cause of the problem.

1.2.2. Digital Twin, Augmented Reality, Virtual Reality

At present, the term digital twin is understood primarily as a virtual representation of physical objects, both production and transportation equipment, but also processes, systems, workers or the entire environment. The digital twin is thus no longer just a virtual model of the real counterpart, but a dynamic carrier of data and status information obtained through a number of sensors and sensors connected by the Internet of Things.

The digital twin can thus be used to monitor physical objects and processes in a real environment and time. The advantage of this approach is the creation of a detailed digital image with real data. It can then be used in complex simulation models, where it contributes to the acceleration and facilitation of decision-making processes, because it eases the direct identification of possible consequences of the considered changes and key patterns of behavior in individual processes. Here it is necessary to emphasize that it is possible to simulate the interaction of the human operator and to solve the arrangement from the ergonomic point of view before putting it into real operation. Simulation using a digital twin also brings deeper knowledge about the causality of individual components in processes and environments, allows to identify weaknesses that need to be stabilized and optimized in order to increase process performance and strengthen the robustness of the environment.

Virtual (digital) copies of production equipment and lines can be used for predictive maintenance. They can also be used for operational, planned, corrective and preventive maintenance. In this context, it is also necessary to mention other possible uses, for training operators and service personnel. Here, the possibility of using virtual reality has its irreplaceable role, which in combination with simulation tools will prepare a very realistic perception. In this way, a number of standard and non-standard situations can be trained, which can be expected in production and maintenance. Because in fact some phenomena may occur with a very low probability, the individual may not encounter them for a very long time. However, he/she should be prepared in training so that he/she is able to react correctly and perform adequate actions.

1.2.3. Additive Manufacturing (3D Printing)

3D printing, or additive manufacturing, is the construction of a three-dimensional object from a CAD model or a digital 3D model. Some advantages of 3D printing for industry are that 3D printing can print many geometric structures, as well as simplify the product design process. It is also relatively environmentally friendly. In low-volume production, it can also decrease lead times and total production costs. Moreover, it can increase flexibility, reduce warehousing costs and help the company towards the adoption of a mass customization business strategy. In addition, 3D printing can be very useful for printing spare parts and installing it locally, therefore reducing supplier dependence and reducing the supply lead time [4].

1.2.4. Internet of Things

The Internet of Things (IoT) is a new trend in the control and communication of objects of common use with each other or with humans, especially through wireless data and Internet technologies. Such interconnected devices enable the collection of large amounts of data that can be further processed and used in various areas such as logistics, healthcare, energy, transport, meteorology, etc. The term "Internet of Things" is just an umbrella phrase. Already today in practice, countless devices such as remote-controlled appliances (sockets, lighting), cameras, weather stations and individual sensors work. However, they do not yet cooperate under one technology and a common protocol.

In the manufacturing process, sensors and more complex systems classified as Internet of Things can be used for a variety of purposes. The main ones are monitoring the condition of machines and equipment (see below - predictive maintenance); movement of material, intermediate products and final products in production and storage; monitoring of the state of the environment (measurement of temperature, humidity, oxygen content, carbon dioxide, or undesirable substances according to the nature of production); monitoring the activity of operators (e.g. interaction with production equipment). The obtained data can be used both retrospectively and prospectively. Retrospective use is possible, for example, for the analysis of the speed / slowness of production, defective products, and bottlenecks in production. Using artificial intelligence algorithms (see below) allows to prepare detailed analyzes and reveal information hidden in the data, which is not completely clear, for example, from time series. Prospective use is offered in the design of a new product or the integration of a new machine using a digital twin and a simulation system (see above).

Another promising area of IoT utilization is predictive maintenance. The basic prerequisite for predictive maintenance is a suitable design for data collection from production facilities. This means using data that can be provided directly by the device, as well as data from suitable complementary sensors or other IoT elements that will measure other quantities on the device or in the environment. Other information about operation or faults in the past can be also used. This information can serve as additional input to machine learning algorithms and thus improve predictions. However, it should be emphasized that machine learning methods must also be chosen appropriately depending on the nature of the data obtained (see below).

Unlike preventive maintenance, predictive maintenance based on machine learning can recognize degradation patterns long time before the actual failure and predict impending failures. Thanks to this information, the operability of the equipment is extended, downtime is reduced and the most fruitful improvements are achieved in terms of the overall efficiency of the equipment, which guarantees manufacturers the highest lifetime return on investment. Predictive analytics and machine learning software achieve this through programs that run continuously. They distinguish between the normal and unusual state and behavior of a device or process by recognizing complex data patterns that reveal accurate degradation and failure signals. The tasks that these programs perform are of two types. One type acts as a detector of anomalies and deviations from otherwise normal behavior. The second one detects real patterns of faults and identifies behaviors that result in specific faults. When detecting unusual behavior or patterns of failures, machine learning programs send alerts not only weeks but sometimes months before the failure itself and prescribe specific corrective actions. As a result, we are able to avoid production downtime, repair minor defects that could subsequently cause major problems, reduce downtime costs, and provide operators and maintenance personnel with confidence in predicting failures, giving them time to eliminate basic causes of equipment failures. Such an automated approach, which inserts and abstracts the details of machine learning techniques, is significantly more efficient and accurate than other systems that currently exist in equipment maintenance.

1.2.5. Robotization

Robotization as such has higher ambitions today than simply replacing humans with machines. In particular, it is a highly flexible system that connects the product configuration system, ERP (enterprise resource planning) and robots that are able to produce the product according to the digitized assignment. Robotization thus moves certain production processes to a completely different level - qualitative, quantitative from a number of points of view, including health protection during production and production safety.

Other attributes of robots are their accuracy, reliability, low risk of error and time savings. They allow easier standardization than manual work. In this way, they contribute to reducing costs and maintaining production parameters and product quality. Another important functionality is automatic quality control. In the standard arrangement, quality control has been performed by a person, usually only optically, or by re-measuring the product. However, this entails a relatively high error rate, given the human factor (oversight of the wrong product, inaccurate measurements, laziness, etc.).

In new arrangements, the inspection station is supplemented by various sensor systems, which automatically inspect the products and can therefore accurately evaluate whether the product corresponds to the required quality or not. In addition, this data is automatically transferred to the superior ERP / MIS (management information system) and thus allow long-term monitoring of production quality in relation to other parameters, including the quality of input material, production process, etc.

1.2.6. Big Data

Currently, standard tools available in management information systems are used in most cases. The reason is also that there is not yet such a data flow from production that would require the use of systems for the analysis of large data. Online records at the terminals of individual machines are used for statistical evaluation.

Introduction of sensory systems and IoT assumes continuous data collection from operation for subsequent multipurpose use. Therefore, long-term storage of both raw data and aggregated information is necessary. The aggregated information can be used for a quick overview of past states and solutions. Raw data allow the deployment and testing of methods that may not be available when starting a new operation. At the same time, this data will be used to continuously "train" the artificial intelligence methods used.

The first step is high quality data and functional analysis that helps identify suitable systems for managing large data. Equally important is the design of data structures for storing data so that their extraction is as easy and efficient as possible.

An example of the systems producing large volumes of data is a system for on-line monitoring of some quantities, especially technical failures and consumption of spare parts within predictive maintenance, monitoring of product quality and the share of scrap, as well as the share and development of production waste. All monitored data can be used in the optimization of production and predictive maintenance using artificial intelligence algorithms.

1.2.7. Use of Artificial Intelligence Algorithms

Selected artificial intelligence algorithms can be used for multiple purposes in the production environment.

The first large part is the area of production planning and scheduling [5]. For example, planning and scheduling methods with constraints can be used (constraints are spatial, temporal and capacity - there is no unlimited space, infinite time or infinitely large capacity of production facilities or human resources). These methods are usually supplemented by optimization algorithms, because one of the goals is to find the most suitable of more possible solutions according to the selected criteria (time, finance, energy, material consumption).

The second major area is the use of machine learning methods [6]. This mainly concerns production and maintenance. Given that after the deployment of new technologies (machines and IoT), there is not enough input data at the beginning, which is required by most machine learning methods, it is advantageous to use the case-based reasoning method [7]. It allows to work with a small number of "cases", in which we can incorporate the formalized knowledge of experts about the operation in a suitable way. Part of the case-based reasoning is a library of typical cases describing individual categories of states or situations (e.g. normal state of the machine, minor deviations from the normal state, larger deviations from the normal state, state close to failure, failure). Each newly confirmed pattern in the data can be added to the library and thus constantly refined.

After a sufficiently long collection of data from the operation, it is possible to learn selected machine learning methods from this data and possibly fine-tune on the basis of a library of typical cases created by the method of case-based reasoning. The basic considered methods of machine learning are SVM (support vector machine), neural networks, and decision trees (or in the variant of decision forest optimization). The final decision is related to the nature and volume of the input data.

1.2.8. Cyber Security

From our point of view, cyber security refers to the physical security of data repositories, communication lines within the company, data security and processes ensuring compliance with cyber security standards [8]. The physical security of data warehouses seems relatively simple. For communication lines, it is necessary to ensure secure transmission of data and information. Data can be secured by appropriately selected encryption, documents e.g. by electronic signature. This technical security must be accompanied by the introduction of cyber security standards and strict adherence to working procedures. Due to the fact that ERP / MIS stores standard production data and personal and payroll data of employees, standards required for data security and their transmission in standard environments (Cyber Security Act, Personal Data Protection Act and GDPR) are introduced. One of the options that a company can use is to monitor and analyze behavior directly in a protected network (intranet) using artificial intelligence algorithms.

1.3. Summary

Currently we can already find implementations of some parts of the Industry 4.0 concept in the industry. The most frequent ones are in manufacturing with high level of robotization that is implicitly and inherently accompanied with introduction of sensory systems, IoT, continuous monitoring, and thus generating large volumes of data. Still there is open space for implementation of artificial intelligence methods for analysis of these large data volumes. Some above described areas can be found as separate islands that are waiting for incorporation in the whole process flow. Virtual/augmented reality and 3D printing are just two examples. However, even being not connected directly to the manufacturing process they can be part of a distributed solution thanks to transfer of control code to other places.

A wonderful example of this distributed approach to 3D printing and sharing the code for the 3D printers was development and production of the first series of the protective half-mask. Since the very beginning, the goal was to make a prototype that can be produced anywhere in the world on the principles of distributed production. Distributed production allows to compensate the local lack of production capacities or resources. This way, **CIIRC RP95-3D** was produced (https://www.ciirc.cvut.cz/covid/).

We have described in more detail those parts of the Industry 4.0 concept that have the potential to be applied successfully in the health care environment.

2. Health Care

Current health care is characterized by continuously growing costs and by technology development and digital transformation. One of the main reasons why the health care costs are growing too fast is increased life expectancy that leads to a much higher level of chronic diseases. Other reasons are inefficiencies in the health care system, more frequent demand on care, inflexible care settings, inefficient and insufficient use of medical technology and advanced data processing, low stress on prevention.

When we analyze the state in detail, we can find many similarities with the industry, although we have to keep in mind that not all processes in health care can be automatized and that large portion of the activities will be always performed by humans. However, they can be better supported by technology, data and information in their work. The Covid-19 pandemic showed the need of technology in many areas of health care activities. In some cases, it speeded up development and introduction into routine operation of various devices and tools. Excellent examples are laboratory robots performing monotonous repeated simple, but precise operations; mobile robotic platforms with special body containing UVC-LD unit for disinfection [9]; Lab on Chip solutions for prompt diagnostics. The situation also proved that more intensive use of telemedical applications for distant monitoring of patients is needed. Many chronic patients were isolated at home and were afraid to visit their doctors because of the possibility being infected. In these cases, telemedicine can help. On the other side, it generates large volumes of data that cannot be evaluated manually. The disciplines, such as Big data and artificial intelligence offer tools for handling the problem.

In the next paragraphs we touch the areas described in section 2.2 and show, which of them are already used and/or what is the current research in the respective areas.

2.1. Selected Items of Industry 4.0 Concept in Health Care

2.1.1. Data integration

In health care there are many activities that need proper planning and scheduling. It starts from shift planning in hospitals, nursing homes and similar institutions, over planning and scheduling of examinations and treatments on special devices (e.g. CT, MRI, and nuclear medicine), operations, patient visits. Although there are already some positive examples where advanced algorithms are used, these planning tasks are done mostly manually. It is highly desirable to transform planning and scheduling tasks to digital form, utilizing advanced algorithms.

Monitoring in health care is represented by two tasks: one is monitoring of medical devices and the other one is monitoring of patients [10, 11]. Devices have to be checked regularly (so-called safety technical check), the procedure is defined by legal regulations. However, between the checks the devices are usually not monitored by additional sensors that could indicate any problem. Only if the device has self-check function integrated. Thus similar approach to industrial monitoring is highly advisable. Continuous monitoring of patients is regularly performed at ICU. If a patient is moved to a standard room, continuous monitoring is not generally performed although there are situations when the continuous monitoring might help identify a health problem faster, thus invoking faster medical action. Discharged patients are not monitored at all (there are few exceptions due to used devices – pacemakers [10, 11, 12] insulin pump and continuous glucose monitor [13, 14]). Obviously, there are more diagnoses, at which continuous monitoring of the patient health state could provide valuable information before a serious state occurs. Sometimes even a simple solution using messaging proves to be useful [15]. Monitoring can be an efficient tool for preventive and predictive medicine.

2.1.2. Virtual reality

Virtual reality (VR) is not yet used in medical practice however it already proved to be a good tool for teaching and training [16, 17] on one side and also for some experimental treatments.

In clinical courses, VR helps in training special skills, simulating situations and states that might occur in real life but training cannot be performed on real patients because they are not available at the given moment (having the required diagnosis, injury, health state, rare disease, etc.). There exist simulators (artificial patient) however they are expensive and some functions cannot be simulated on them easily or at all. VR can simulate almost everything. And moreover, more students can work on the same task at the same time. Last but not least it allows recording all performed actions that can be successively replayed, analyzed and evaluated. It is very important to explain students whether everything they did was relevant and corresponding to the patient state or what was done incorrectly and why.

Rehabilitation, pain alleviation [18, 19, 20], activation of elderly and cognitive training [21, 22, 23] are among the most frequently researched areas. Some of them were already subject to clinical studies. Recently various studies have been performed that examine the potential of VR systems in rehabilitation as the most promising medical application area. Concerning medical diagnoses, most studies focused on stroke, Parkinson's disease and joint replacement. Similarly, to other research of technologies applied to health care, one of the research goals in VR is personalization that allows adjustment of the application to each person needs and abilities during the treatment.

2.1.3. 3D Printing

3D printing and additive manufacturing is a fast growing area that has already found its place in medicine through many applications. Similarly to VR, in education of medical students – in case of lacking anatomical material for study, exact copies can be printed to show students not only normal structures, but also abnormalities that are rare. Currently, 3D printing is more and more used in clinical practice. This development started in 1990s with anatomical modeling for bony reconstructive surgery planning. Next step was development of personalized implants. Liaw and Guvendiren [24] bring an excellent overview of both routinely used applications and research activities in 3D printing for medical purposes. Dentistry is the area where 3D printing is used almost routinely for prostheses, dentures, dental models and surgical guides building on high degree of accuracy of printed products and patient-specific design. Research and development activities can be found in the areas of medical devices, tissue engineering scaffolds, tissue models, drug formulation and controlled drug delivery [25, 26]. 3D printing uses various technologies and printable materials. One of the advantages is the development of complex geometric structures impossible to produce by standard manufacturing technologies. The potential of 3D printing is high. However, there are still open issues of clinical trials, approvals and legal regulations because till now the patient-tailored design in its depth and manufacturing the printed product directly at the point-of-care were not considered.

2.1.4. Internet of Things

Recently with the aim to distinguish IoT applications in medicine from other areas, the term Internet of Medical Things (IoMT) has been introduced. It represents the interconnection of medical devices and their integration to a wider network with the aim to collect and analyze larger volumes of patient data to improve patients′ health. Currently there exist many forms and types of IoMT that are used to some extend in practice. For example, wearables used for measurement of physiological parameters belong to them. Some types of ambient sensors can provide useful information about the patient state as well. Obviously, if we want to rely on the data precision in the same way as in case of the data coming from certified medical devices, there might be an issue. However, we need frequently the information about the trends and not exact values. For such purpose most of these fitness bracelets and similar products are sufficient. Gatouillat et al. [27] and Al-Turjman et al. [28] present in their reviews existing types of IoMT, their architectures, challenges, concerns and research directions with the focus on the technological side. Major concerns that need to be addressed are reliability, precision and accuracy, security and privacy, energy efficiency. Interoperability and modularity are mentioned only briefly without deeper analysis of requirements on data formats, data models and standards. Ethical and legal issues are not discussed although they are very important for wide acceptance and introduction of these technologies into routine practice [29].

2.1.5. Robotization

Robots cannot fully replace human medical doctors and nurses. However, there can be identified many demanding and tedious types of work where they can either replace or at least assist a human. In some hospitals autonomous robots are already used for transportation of material, laundry or meals, mostly only on technical floors [30, 31]. The reason is to avoid potential accident with patients or staff. Autonomous robots or manipulators with arms as known from the industry are not used in health care. Recently there have been developed several projects focusing on social robots that can serve as companions to patients [32, 33]. Due to Covid-19 several interesting applications were developed: laboratory robot based on industrial platform for precise manipulation with samples, mobile robot with body wearing the UVC-LD for space disinfection [9].

2.1.6. Big Data

Medical technology already generates large volumes of data. The greatest problem that must be solved is connected with current fragmentation of data. Data from different modalities are stored separately and it is impossible to integrate them and to perform analysis of complete data of a single patient in one system. If we add data from continuous monitoring, we could get a very rich picture of the patient health state. However, this task needs more research in advanced data models that would be able to encompass all data types. In biomedical image processing, many advanced algorithms have been already introduced [34]. Recent development in deep learning seems promising as some publications show. But, as shown in [35], proper data preparation and selection for the training, testing and validation sets is crucial. At the end of the day we get either an excellent model that identifies objects in the images successfully or a model that fails at an image, which a child recognizes. Therefore, the greatest challenge is proper understanding the primary acquired data and selection of the relevant methodology and finally selection of the most suitable processing methods.

2.1.7. Artificial Intelligence

Many AI algorithms have been used in particular for image and signal processing, and data classification in different medical tasks [36, 37]. However, they are still subject of clinical research and are not frequently used in everyday practice. In some cases, they are directly incorporated in the software of a device and give recommendation of the diagnosis. This is the case of current ECG devices.

With the large volumes of incoming data use of AI algorithms will be inevitable. Without any doubt, the developed software has to be tested thoroughly if the intended use is decision support. The challenges are the same as with big data.

2.1.8. Cyber Security

Since the health care systems work with sensitive data, the requirements on data privacy and security of all systems are very high. When compared with the industrial environment, it is more challenging to ensure security in health care because there are more users that need access to various interconnected systems. The security measures must be strictly followed by all actors in the health care field. On the contrary to the industry, there are many more persons accessing the sensitive data and information. Many devices were not primarily designed for work in a network environment. Telemedicine and IoMT must operate in the Internet. All these aspects contribute to increased vulnerability of the interconnected systems and their parts. Human errors (sometimes even intentional misuse) are one part of the problem, which can be reduced by education and training to some extent. Currently, cyber-attacks coming from the Internet become more frequent and represent more serious threat. The task is then to detect pirated software, malware and infected files across the IoMT. Ullah et al. [38] proposed a detection method based on deep learning approach that is able to identify malware with very high accuracy (more than 97%). Another critical issue is secure communication from the sensing device to the storage and/or processing site. One of the possible solutions is proposed by Deebak et al. [39]. It utilizes a secure anonymous biometric-based user authentication scheme using smart card. As mentioned above, IoMT devices and systems are inherently vulnerable. They frequently combine wide variety of technologies, including wireless sensor networks that are inherently insecure. Moreover, healthcare manufacturers and users are frequently not aware of IoMT security risks. There is lack of security standards for IoT in general. Recent activities have been aimed at assessment of degree of security provided in IoMT solutions [40]. The authors proposed a security assessment framework for IoMT solutions that is available as web application.

2.2. Summary

In some aspects health care is similar to industry. But there are also many differences, in particular due to the character of work. In health care the human-human interaction is the major type of interaction, in the industry human-machine interaction (and machine-machine interaction) prevails. Diagnostics and treatment are more personalized – each patient is different. Industrial production builds on standards and norms, which makes also the data collection and processing easier. Health care uses medical guidelines however they are written in natural language. The degree of formal descriptions in medicine is still rather low. Most of the patient history and treatment recommendations is recorded as unstructured free text. This complicates successive analysis that should utilize this information. The requirement of structured electronic health record is a necessary condition for use of more advanced algorithms that could combine data from different modalities with descriptive information in the record.

3. Conclusion

In the paper we tried to describe the basic characteristics and parts of the Industry 4.0 concept and identify those ones that are already used or could be introduced in the health care area. We see still as main problems the huge variability of data formats, no unified approach to information systems design, closed data formats of medical devices (processed and visualized by proprietary software without possibility to store the raw data and results in patient record). From this point of view, standardization and interoperability remain the main challenges. Interoperability and standardization need to be elaborated in relation to data and aggregated information. Thus, it is not enough to be able to receive the message, i.e. to understand the syntax of the message, but it is necessary to understand the semantics. This requirement implies development of a data model that maps semantic content from the data received from the devices into an information system that is usually used for collecting and evaluating data from monitored persons. It must be based on several relatively simple principles: creation of formats and protocols for exchange of data records between health care information systems; format standardization and connected interface unification; improvement of communication efficiency; guide for dialogue between involved parties at interface specification; minimization of different interfaces; minimization of expenses for interface implementation; keeping rules of ethical conduct; and strictly following the legal regulations.

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