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REVIEW

Advances in Wearable Electronics, M-IoT, and Artificial Intelligence for Medical and Healthcare

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ABSTRACT

The integration of electronic and digital technologies into the medical and healthcare sectors has profoundly reshaped the way healthcare is delivered, monitored, and managed across diverse clinical settings. Technological advancements have led to the development and widespread adoption of innovative tools such as medical devices, diagnostic platforms, health monitoring systems, telemedicine solutions, and electronic health records (EHRs), all of which have contributed to improved patient outcomes, streamlined operations, and expanded access to healthcare services, particularly in underserved regions. This paper presents a comprehensive literature review of recent breakthroughs in medical and healthcare technologies, emphasizing the most transformative developments and emerging trends. It explores critical domains including wearable health monitoring devices and biosensors, robotic-assisted surgery, digital health interventions during the COVID-19 pandemic, the Medical Internet of Things (M-IoT), smartphone-based healthcare applications, and the growing role of social media and blockchain in medical data sharing and security. By examining a range of technologies and their integration into clinical practice, the review identifies key strengths, practical challenges, and areas of potential growth. Comparative analyses of different systems are provided to assess their relative effectiveness, usability, and scalability. Ultimately, this review seeks to offer a thorough and accessible overview of the ongoing digital transformation in healthcare, contributing valuable insights for researchers, practitioners, and policymakers alike.

Keywords: Electronics; Medical Devices; Healthcare; Social Media; Wearable Sensors

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1. Introduction

Electronic and digital applications and systems are increasingly used in medical and healthcare fields. A thorough and comparative review can provide a useful perspective, benefiting researchers in this area. While some reviews cover aspects of digital healthcare and medical electronics, there is a lack of in-depth comparison of different applications. For example, in the work by Neuman et al. [1], medical devices from the last 100 years have been reviewed, discussing medical imaging, nuclear medicine imaging, modern surgical techniques, and biomedical sensors. The implantable medical electronics have been discussed in 23 chapters in [2]. Some other recent works show a review on the recent digital healthcare systems, such as references [3–5].

This paper reviews the most recent electronic and digital applications and systems in medical and healthcare fields. It covers key topics such as wearable electronic applications, the Medical Internet of Things (M-IoT), electronic healthcare record systems, smartphone applications, Artificial Intelligence (AI), flexible hybrid electronics, electronic and digital healthcare during COVID-19, medical sensors, social media and websites, Blockchain technologies, electronic drug delivery systems, Nano-BioElectronics, and robotic surgery systems.

To provide a stronger theoretical framework, this paper draws upon the Technology Acceptance Model (TAM) and the Socio-Technical Systems (STS) theory to explain the integration of electronic and digital systems in healthcare. These theories suggest that the adoption and impact of medical electronics depend not only on technological capabilities but also on user perception, infrastructure readiness, regulatory environments, and healthcare delivery needs. From an economic perspective, digital and electronic healthcare technologies can improve efficiency, reduce operational costs, and increase access to care, particularly in underserved regions. The relationship between technology and healthcare outcomes is bidirectional: while innovations drive better diagnostics and treatment, the specific needs and constraints of healthcare systems also shape the development and application of technologies. Causality is often dynamic—new medical challenges prompt technological solutions, which in turn create shifts in healthcare practices, cost structures, and policy [6–8]. This paper explores these interdependencies while comparing specific technologies.

The paper compares the advantages and disadvantages of various aspects, including social media and websites in medicine, robotic surgery systems, and medical data management systems using blockchain technology. Additionally, it includes other comparisons that provide a useful perspective in the field.

2. Wearable Electronic Applications

The evolution of technologies like flexible hybrid electronics has been the driving force for constructing miniaturized vital sensors, helping people maintain their physiological well-being and monitor their diseases. One of the branches that grew out of the idea of applying biomedical devices in wearable objects (especially textiles) is Textronics. Textronics (or "Smart textiles") is an umbrella term for a diverse range of textile-based devices serving different functionalities, e.g., sensing, communication, energy storage and harvesting, heating, etc [9]. Disregarding the purpose of textile-based devices, they are manufactured similarly and use similar resources to incorporate individual components into a system, e.g., conductive yarns [10], functional fabrics [11], or inkjet printing of conductive onto a piece of cloth [12]. This group of devices can be divided into two groups: passive and active. Passive smart textiles can sense the environment but not actively react to external stimuli. Typically, they don't require an external power supply. Active groups are appliances integrating actuators or some implemented logic to perform reactive sensing and interact with the outer world. This category generally uses an external power delivery system or contains an energy storage/harvesting mechanism [13].

2.1. Internal Structure of Devices

Textronics, as opposed to classical electronic devices, are characterized by technologies that perform certain circuit features like interconnections, antennas, and sensing functionality.

Previously, conductive fibers were used in many different areas, such as part of antistatic applications [14], electromagnetic interference shielding [12], infrared absorption [15], or protective clothing in explosive areas [12]. In this particular field, they found usage as an interconnection medium. A further step in developing technology for conductive yarns was incorporating them into larger, more complex fabric structures. The simplest structure of incorporating conductivity with a fabric is, e.g., weaving the material out of yarn wires described in the previous chapter [16]. The next generation of conductive fabric was born in the Electronics Department and the Wearable Computing Laboratory at the ETH in Zürich. The new material (PETEX) consists of a grid of copper alloy wire (with a diameter of 50±8 um) separated by fibers of woven polyester monofilament polyester thread (PET) [16].

2.2. Vital-signs Data Processing — Data Mining Methods for Wearable Devices

One of the most significant impacts on the wearable electronic area was the growing computational possibilities of miniature System on Chip (SoC) solutions. Researchers have recently moved from simple data collecting towards more complex processing systems like those based on neuronal networks, classifiers, and mathematical signal processing methods. Predominantly processing systems implemented in wearable electronic devices can be categorized into three groups based on their targeted operation [17]:

- Estimation of future patients' physiological well-being based on measurements.
- Abnormality detection of bio-indicators collected by sensors.
- Diagnosis based on the characteristics of individual diseases and the best fit for the collected data.

In the context of prediction, diagnosis, and decision-making solutions, such systems are designed as a bigger or smaller variation of what is given in **Figure 1**. Shown architecture is a basic example of machine-learning algorithm implementation in wearable devices. The whole chain consists of various stages, including pre-processing, feature extraction or selection, and application of a machine-learning model. The diagram illustrates a smart wearable system architecture designed for data-driven decision-making using sensor-based machine learning. In this framework, sensor data from wearable devices undergoes a pre-processing stage to clean and normalize the raw input, ensuring consistent quality for further analysis. This is followed by feature extraction and selection, where relevant attributes are derived to represent the underlying physiological or activity patterns. During the training phase, these features, combined with expert knowledge and metadata, inform the modelling and learning process to develop a predictive model. Once trained, the model is applied to new (test) sensor data to perform real-time detection, prediction, or decision-making, enabling responsive and intelligent behaviour in smart wearable systems. This architecture supports applications such as health monitoring, activity recognition, and early anomaly detection [17].

2.3. Prediction of Patient's State

Estimating future events influencing the general health state is a primary task of preventing diseases, allowing detection of early symptoms of worsening well-being, and giving a chance to perform actions before developing severe health conditions. The most common realization of this approach is that learning models (like the temporal abstraction model used in the mentioned studies) are trained on large sets of sampled data, such as heart rate during various situations, blood oxygenation, etc. [18]. Examples of such implementations of predictive algorithms can be brought:

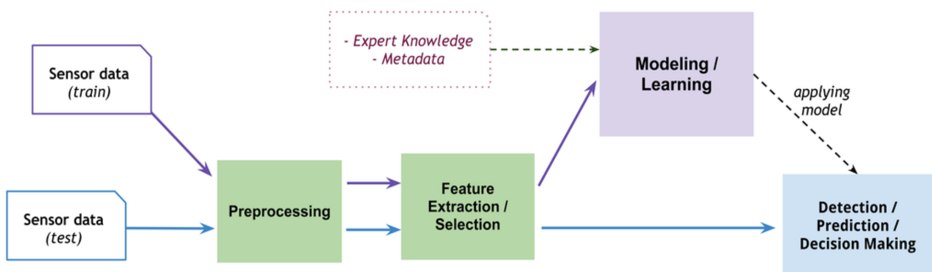

Figure 1. Basic Implementation Model of Decision-Making Used in Wearable Applications. Reprint is in Accordance with the Creative Commons Attribution 4.0 International License [17].

- Body area network (BAN) consisting of various types of sensors implementing a prediction model of someone's future stress level [19].
- A complex glucose level / physical activity monitoring system utilizing data from ambient sensors across the house, wearable sensors, and data collected from blood glucose monitor devices [20].
- Model of predicting hemodialysis patients' general well-being and estimation of hospitalization risk of individual [21].

2.4. Diagnosis Methods and Abnormality Detections

Wearable hardware utilizing data mining shows the supremacy of its construction as a diagnostic tool with constant monitoring functionality. The task, in contrast to the previously mentioned one, is more sophisticated due to the complexity of the whole system based on more complex data, including detected patterns of abnormalities from bio-sensors or patients' medical reports [22]. However, one of the most frequent solutions for implementing such a decision-making model in the diagnostic process is implementing some classification method like a Neuronal network or decision tree [23,24]. Examples of wearable systems fulfilling diagnostic needs can be an automatic diagnostic system for:

- Coronary artery disease, by deducing further health information from heart rate patterns [19]
- Apnea based on ECG and blood saturation patterns [20]
- Insomnia, sleep fragmentation, and disorders in the sleep macrostructure by performing polysomnography [25]

An essential part of the diagnostic approach is high-quality data with the least amount of artifacts in sensor signals. Among the available methods for the preprocessing stage are:

- Threshold-based methods.
- Statistical tools allow the interpolation of lacking data points.
- Classical signal processing approaches include Fourier analysis and low-pass/high-pass filtering of incoming sensor signals.

Final data after preprocessing are necessary for the last part of the mentioned data mining functionalities, abnormality detection. Depending on the implementation, the algorithm searches for irregularities in an incoming signal or compares it with the predefined dataset, and, based on this information, it judges a patient's health state in real time.

2.5. Wearable Sensors

A crucial element of any health-related wearable system is its ability to measure biomarkers and bio-indicators, providing reliable information about the patient. Also, recent years have brought us new designs and constructions, allowing us to extend available measurement principles of biosensors.

2.6. Optical Sensors

One of the major categories of detectors measuring biochemical response is based on the optical properties of a tissue or bodily fluid, like Raman scattering, fluorescence, or colorimetric.

2.7. Colorimetric Sensors

Colorimetric sensors work on the principle of the light's wavelength shift of the material's absorption spectrum in response to chemical compounds in the environment. A typical application of this method is an absorbent epidermal hydrogel-based patch infused with active substances like tannic acid or polyacrylic acid [26].

Typical applications of this technology are ions and biomarkers detection in bodily fluids (e.g., sweat), like in a proposed system where the proposed solution was directed onto the detection of glucose and enzymatic oxidation by sampling patients' saliva [27,28].

2.8. Fluorescence Sensors

Fluorescence sensors are detectors relying on a fluorometric agent encapsulated with a sample. The presence of target analytes like glucose, chloride ions, sodium ions, or zinc ions influences the light intensity of sensors [26]. One example of Fluorescence-based measurements in health monitoring is a Smartphone-coupled dermal sensor analyzing sweat concerning glucose, lactate, chloride, pH, and volume [29].

2.9. Photoplethysmography (PPG)

Photoplethysmography is a method of measurement based on light passing through a tissue or internal organs like veins or arteries and an approximation of their properties considering their absorption. By utilizing PPG, it is possible to detect the oxygenation level of veinous blood and pulse rate classically, like pulse rate monitors, a common measuring technique [30].

2.10. Interferometry

Interferometric sensors detect changes in optical length path, phase shift, or polarisation of light in contact with analyzed tissue. A common way to implement such a method is by incorporating in the structure different types of micro-interferometers like Fabry–Perot and Mach–Zehnder or by using another technique of measuring optical length paths like Bragg grating [22,31,32]. This broader type of optical sensor also finds its place in a wide spectrum of bio-measurements like blood pressure monitoring [31], cardiovascular complex diagnosis systems [32] or respiratory monitoring [33].

2.11. Pressure Sensors

The clinical approach of utilizing various sensors was initially focused on performing investigations like ECG, EMG, and EEG. In the case of pressure sensors, their major application was a part of blood pressure measurement equipment. In recent years, the arsenal of available applications was widened by further research, and pressure sensors were found to be also used in early-stage Parkinson's disease detection [34], intracranial pressure measurements or arterial stiffness diagnosis [35,36]. **Table 1** summarizes research conducted in terms of optical and mechanical sensors and their area of usage [27,29–31,34,37–45].

Table 1. Summary of Conducted Research in Terms of Optical and Mechanical Sensors with Their Area of Usage [27,29–31,34,37–45].

Principle of working	Type of sensor	Application
Optical	Colorimetric	Detection of ions and other bio-indicators in bodily fluid [27,37]
	Fluorescence	Detection of ions and other bio-indicators in bodily fluid [29,38]
	Photoplethysmography	Pulse detection, oxygen saturation, volumetric flow of blood [30]
	Interferometric	Temperature, relative humidity, monitoring respiration and cardiac actions, blood pressure [31,39,40]
Mechanical sensor	Piezoresisticity	Cardiology, motion activities [41,42]
	Capacitance	Cardiology, intracranial pressure, early-stage Parkinson's detection, muscle movement [34,43]
	Piezoelectricity	Cardiology, arterial stiffness, Dermatology [44,45]

3. Medical Internet of Things (M-IoT)

The Internet of Things, also known as IoT, is the next step towards the evolution of the Internet. The fundamental concept of this network is to collect, share, and process data without human supervision. Although the World Wide Web was invented by Tim Bernes-Lee in 1989, some people believe that the first example of an IoT application was created in 1982 at Carnegie Mellon University. After several improvements had been made, a local Coke machine was ready to report the amount and temperature of the beverage inside [46].

Such an opportunity to create a system that could extend diagnostic – this time with full-time tracking of patients' life parameters - led to the introduction of IoT to healthcare. That brought numerous benefits, including remote monitoring, lowering medical personnel expenses, more personalized care, and even supporting surgeries [47].

Long-term tracking systems allow for data collection and finding unobvious physiological reactions that may be an early sign of a developing disease. The following sections illustrate some recently created IoT solutions that answer current medical challenges.

3.1. EOG Glasses

Scientists emphasize the importance of monitoring Eye Blinking (EB) in people at risk of neurological diseases such as Alzheimer's and Parkinson's [48]. EBs can be counted by measuring potential between two sides of the human eye (the front and the back). To achieve that, the Italian-German scientists created a prototype of glasses equipped with electrodes that form a simple ElectroOculoGram (EOG) [49]. The noticeable drawback compared to traditional EOG systems is the placement of electrodes: usually, they are supposed to be in specific areas of a face. However, it is compensated by comfortable placement for long-time data gathering. The position is a natural consequence of contact points between the glasses and the patient's head. The comparison between these two approaches reveals that satisfying results of Eye Blinking tracking can be obtained by both optimal configuration and glasses configuration with adapted filtering.

3.2. Wireless EEG

ElectroEncephaloGraphy is a non-invasive method of monitoring brain activity. Conventional EEG devices consist of many electrodes attached to the scalp during the examination. Scientists developed an ear-EEG technique to overcome the inconvenience of extensive equipment preventing long-time data acquisition. It involves placing electrodes in the area in or around an ear, which provides skin-to-electrode contact (without excessive hair), the comfort of use and enables sleep monitoring and emotion recognition. The main challenge of this solution is its size, which imposes restrictions [50].

3.3. Pandemic Monitoring

The development of IoT systems is also connected with the COVID-19 pandemic. It affected several areas of applications, including:

- Detection of diseases at an early stage
- Full-time monitoring of infected people
- IoT-based neural network systems that predict the pandemic development [51].

3.4. Fog Computing

The development in the M-IoT field is more than just a growing number of applications. This is only possible with the growth in recent technologies, such as fog computing.

Fog computing, also known as edge computing, is a service created to improve the efficiency of a network while processing an exponentially growing number of data coming from sensors. Instead of conducting all the operations in a cloud, several computations are moved to the edge of an infrastructure - close to the data source [52]. An application can be divided into three layers: the thing, the fog, and the cloud. Although the cloud layer would be responsible for providing the data for both deep automated and human-performed analysis, the fog layer would give the service response time needed in emergencies [53]. This is why this technology became an answer to challenges in healthcare, in which time is a crucial factor in saving human life.

Let us consider an example of a framework designed to predict diabetes [54]. It performs calculations on both mentioned levels. The cloud is responsible for making predictions in association with machine learning. According to [54], it reaches an accuracy of almost 90%. However, this procedure takes time. To improve the level of analysis, the implementation was equipped with the fog component that provides real-time verification using fuzzy logic. Although it reached an accuracy of only 64%, it significantly developed tool capabilities.

Moreover, energy consumption is a crucial issue that needs to be considered by an engineer during the design process. One of the solutions for IoT devices is to reduce data transfer, which requires postprocessing to reconstruct the original information [55]. Fog computing can be an answer to the problem of compression and filtering of medical images. Files obtained from ultrasound, magnetic resonance imaging, or computed tomography, usually containing 3D pictures, are extensive. A high compression ratio, a crucial factor in lowering network traffic, can be reached shorter if more techniques are added to the fog layer rather than other components [56].

Considering all the examples, several crucial improvements brought by M-IoT can be named:

- Real-time analysis
- Comfort of use in long-time data acquisition
- Remote monitoring.
- On the other hand, the challenges for further development are:
- Low energy consumption
- Improving the analysis' effectiveness indicators.

3.5 Other M-IoT applications in healthcare:

- Monitoring and alarming systems for cancer care [57,58],
- Smart monitoring for heart failure patients [59],
- Orthopaedics applications: collecting data about fractured bones and other deformations, post-surgical recovery [60],
- Colonoscopy diagnosis [61],
- Anaesthetic depth control [62],
- Smart orthodontic brackets [63],
- Pregnancy monitoring systems [64].

4. Electronic Healthcare Record System

Medical records were introduced in 1907 at the Mayo Clinic as a patient-centred system of storing and sharing medical data [65]. Since then, the system has developed and changed its structure and content, but the central concept of its operation has stayed the same for almost a century [65]. Today's medical records play an important role in everyday life. They are not only used as records of the care given to patients anymore but also as means of communication between healthcare teams, as sources of information for research or support for administrative, financial and epidemiological purposes. To provide efficient health care, they must be distributed between many care providers, often in real-time. This need creates many problems that can even have deadly consequences. Approximately every year, more Americans die from preventable errors in hospitals than from breast cancer, AIDS or motor accidents [66,67]. To reduce medical errors, improve patient safety and care quality, increase healthcare service delivery efficiency and decrease healthcare costs, scientists and researchers began to work on a new system of electronically distributing data [68–70]. The effect of their work, called electronic healthcare record system (ECHR), is officially referred to as a "repository of patient data in digital form, stored and exchanged securely, and accessible by multiple authorised users" [65].

Although works on it have been ongoing for years, the system remains incomplete. One reason for this is that ECHR must combine various applications with different formats and standards, such as data, graphics, sound or video [65]. In principle, ECHR should enable patients to manage their healthcare system with the help of evidence-based clinical protocols and guidelines [65]. Moreover, care should be integrated or shared so that an individual's healthcare is the responsibility of a team of professionals across all healthcare sectors, not just one doctor [65]. In a perfect world, it would be a system that prioritizes promoting wellness over treating diseases by automatically monitoring patients' medical data on an ongoing basis and proposing actions to prevent diseases.

However, these requirements remain beyond the reach of modern ECHR. There are many reasons why ECHR is not working as it is wished and cannot be introduced at a larger scale. One of the most significant issues is under-investment in Information and Communication Technology (ICT), especially in clinical computing. With a lack of political will and government support for development, it is nearly impossible to create a working system for creating and adopting new standards. It is also problematic that many countries still do not have a national master index and, therefore, do not have any consensus on the unique identification of patients [71]. However, the key challenge remains the need for more human resources [71]. Many healthcare workers, especially in South Africa, have not received computer training. This general lack of awareness of the risks and benefits of going with ECHR among healthcare workers and patients creates wariness and reluctance toward the system, making it impossible to introduce beneficial changes [72]. These are only a few challenges researchers must face to make the Electronic Healthcare System fully functional and working. More of them are shown in **Table 2** [65,68,71–73].

Table 2. Challenges That ECHR Researchers Need to Face [65,68,71–73].

Title of reference	Challenges noted in reference
"Delivering the electronic healthcare record for the 21st century" [65]	Need for flexibility of the system so that it can maintain data composed of records structured in a problem-oriented way, time-oriented way, source-oriented way or a combination of these, Under-investment in ICT, Fragmented markets with insufficient revenue streams to support the development of new systems, Lack of standards or their slow adaptation, Multimedia complexity of medical data, Problems with classification, technology and coding, Confidentiality and security problems
"Personal electronic healthcare records" [72]	Lack of awareness and knowledge
"Hospital information systems II" [68]	Reduce the cost of healthcare
"A Review of Interoperability Standards in E-health and Imperatives for their Adoption in Africa" [73]	Need to share data and coordinate treatment on a real-time basis
"The implementation of an electronic patient healthcare record system: a South African case study" [71]	Widely differing levels of the introduction of electronic data management in different facilities, A low degree of sharing, cooperation, and collaboration between facilities, Wariness due to the number of highly published failures that were caused by poor planning or lack of consistent funding, The lack of agreement on unique, individual identifications of patients, Lack of skilled and trained human resources

It is unknown how long it would take to change the medical record system to a system that allows multidisciplinary teams of doctors to coordinate treatment interventions and share data, enabling patients to manage their medical care fully and aware [73]. For now, the impact of most eHealth technologies is either negligible or, at best, modest [74]. One can only hope that in the coming years, ECHR will be developed enough to be introduced into general use, thus changing health care as we know it.

4.1. Diabetes Care Technologies

Recent advancements in diabetes care technologies have significantly transformed disease management, enhancing glycemic control and improving patient outcomes. Continuous glucose monitoring (CGM) systems have replaced traditional fingerstick methods for many patients, offering real-time glucose readings, trend analysis, and alerts for hypo- and hyperglycemic events. These devices, particularly when integrated with smartphone apps and cloud-based platforms, allow for remote monitoring and data sharing with healthcare providers [75]. In parallel, the development of hybrid closed-loop insulin delivery systems—often referred to as artificial pancreas systems—has enabled more automated insulin dosing by combining CGM data with insulin pump delivery algorithms. Clinical trials have demonstrated improved HbA1c levels and reduced time spent in hypoglycemia, especially in type 1 diabetes patients using these integrated systems [76].

Despite the promise of these technologies, challenges remain in terms of accessibility, user adoption, and long-term adherence. Cost and insurance coverage continue to be significant barriers, particularly in low-resource settings. Additionally, disparities in digital literacy and varying levels of user engagement may limit the effectiveness of technology-driven interventions. Continued innovation must therefore be paired with strategies that address these socioeconomic factors [77].

5. Artificial Intelligence (AI)

The terms Artificial Intelligence (AI) and Machine Learning (ML) are used interchangeably sometimes as a name for technology created to make decisions that were only the domain of humans in the past. We can define AI in many ways: machines' ability to communicate with people via 'chat' while not being recognized (the Turing Test), fulfilling the tasks that require human intelligence, systems, and algorithms for classification, decision-making, and research [78]. It comprises several subfields, such as

Natural Language Processing (NLP), Deep Learning (DL), and (already mentioned) machine learning (ML) [79]. The statistical nature of medical issues with incomplete data, personal differences between patients, noisy signals from overlapping diseases, different courses of diseases, etc., is why medicine is one of the main targets for AI tools [80].

5.1. Machine Learning

Machine learning is a technology based on learning from a set of training data to make further predictions about other examples by a machine. ML is a competition for humans for pattern recognition, as it may identify symptoms and diseases that are difficult to grasp [81]. It is applied in fields in which classical computations would be challenging to perform due to the complexity of an issue. However, a large set of input examples is required to teach the algorithms the desired behavior.

ML can be used in image processing for feature extraction [82]. For example, it enables early bone cancer detection from Computed Tomography pictures in DICOM format with an F1 score of 92.68% [83]. It provides segmentation of mammography images for the detection of breast cancer – the most lethal cancer for women [84].

ML is a tool for working with massive data sets. Thus, it is applicable in data mining of DNA [85]. Numerous efficient ML tools analyze heart parameters for successful disease classification [86]. Data mining with ML algorithms was also developed during the COVID-19 pandemic to understand the problem better [87].

Although the future of ML remains unknown, the development of other technologies significantly impacts it. This is why Quantum Machine Learning (QML) was introduced. It is still at an early research stage, but has already been proven to reduce the algorithm's complexity and accelerate the tasks exponentially [88].

5.2. Deep Learning

DL is a subcategory of ML. Its architecture is mainly based on Neural Networks (NN) with multiple layers of nonlinear processing entities – neurons [89]. Such representation allows for more complexity in data processing than conventional methods, which is highly recommended for unstructured, heterogeneous data collected in medical cases [90].

The area of applications of DL is similar to that of ML. It can be used to classify clinical images in search of pathologies [91], extend diagnostic [92], or enhance the value of conventional clinical procedures, such as DL-supported PET imaging [93].

Multi-task Deep Learning (MTDL) is an extension of DL's functionality. This technology aims to perform several operations simultaneously while optimizing loss functions [94]. Most MTDL networks operate on images, and many support examining areas such as the brain, chest, cardiac system, or musculoskeletal [94].

5.3. Natural Language Processing

Natural Language Processing (NLP) is also area of AI. It is a field in which Artificial Intelligence meets linguistics as it is a technology processing text – it explores relationships between parts of language and tries to gain the meaning of phrases [95]. As a significant part of healthcare data is stored in a written form, several applications of NLP emerged: analyzing records for drug discovery, classifying radiology reports without human input, and specialized chatbots for patients [96].

NLP not only covers the need to process existing texts but also can have a generative form. An example of such a Large Language Model (LLM) is GatorTronGPT. It uses ChatGPT-3 architecture combined with training with 82 billion words of clinician texts and 195 billion words from other writing. After six days of training, the model became a tool for synthetic clinical text generation [97].

Artificial Intelligence is a technology widely used in healthcare. The summary of applications of ML, DL, and NLP according to previous paragraphs is shown in **Table 3**.

6. Flexible Hybrid Electronics

In the last century, medicine has undergone tremendous progress, and new approaches to diagnostics and treatment have been developed thanks to the harmonic development of medicine within the technical environment. The invention of the first technological aids like the stethoscope in 1816 or the discovery that freshly invented X-rays could be used to image the inside of the human body (the first X-ray photograph of a hand was created by Röntgen in 1895) were breakthrough events in the history of medicine [98,99]. Nowadays, people are used to the existence of new technological achievements that are related to medicine. One of the novel promising technologies for medical-related usage is devices manufactured using flexible hybrid electronics technology (or FHE for short).

New Technologies of high-density electronic systems accelerate the development of design techniques for devices in various sectors. One of the novel methods is Flexible Hybrid Electronics (FHE). FHE is a new design concept based on a flexible substrate. The critical difference that makes this technology distinguishable from flexible PCBs is the way of treating components of a circuit and methods of integration in a system as a whole. Generally, FHE is based on a flexible interconnecting substrate with printed conducting traces and external elements (like resistors, capacitors, inductors and transistors). This fully additive process opposes conventional manufacturing processes based on subtractive/additive steps like etching or lift-off [100]. The most significant innovation in the new process is the treatment of used ICs in the circuit. Instead of packaged integrated circuits, bare chip dies are thinned (most often using saw dicing and laser ablation until they achieve final thickness of a few micrometers. Finally, in the thinned version, they are placed on a substrate that interconnects them with the outside world and other components on the board [101].

Table 3. Application Summary.

Technology	Application area
ML	pattern recognition, early diagnosis, image segmentation, and disease classification, requires structured data
DL	pattern recognition, early diagnosis, advanced image segmentation, disease classification, improving conventional diagnostic, cases with unstructured data
NLP	classifying data in text format, data discovery, generating reports in a structured format

6.1. Comparison of Variations in Fully Additive and Conventional Subtractive Processes

At the early stages of FHE development, fully additive processes were characterized by high parameter deviations of printed components. This issue was influential, especially for transistors. The most critically affected properties were the mobility of charge and the threshold voltage of OTFT (organic thin film transistor), leading to variations of up to ±30% μ [102–105]. The growth of available processes delivered us new manufacturing methods with low variations, which were the first candidates to compete with traditional subtractive techniques. The lowest reported fully additive-process variations were ±9.5% μ [105]. Unfortunately, due to the high cost of using a silicon wafer as a stencil (which limits its size to 300mm), issues with applying the process on a large scale and high temperatures during the process, those methods were unsuitable for operating with PET as a substrate. A substantial milestone in this field was acquiring variations comparable to conventional processes involving photolithography (±4.7% μ). It was feasible to revise the organic semiconductor material. One of the best promising OTFT materials was a blend of TIPS-pentacene with polymer, e.g., polystyrene dissolved in a solvent complex consisting of toluene and anisole. New material allows for lower variations, increased charge mobility, and better management of the uniformity of semiconductor film [106].

6.2. Challenges to Defeat in the Future

Studies in the domain of Flexible Hybrid Electronics have identified challenges in constructing electrical circuits on flexible substrates. One of the uneasiness in new technology is the influence of convex and concave bending. The main consequence of the actions mentioned above is a variation of the elements' electrical characteristics in the bending radius function [107]. This phenomenon impacts nearly all printed components (resistors, capacitors, and OTFTs). In the context of OTFTs affected, the most crucial transistor parameter is the drain current under specific polarisation conditions. Research reported diverse deviations (from 5% to 118%) depending on the manufacturing process of the device and the Gate-Source voltage applied to the device under test [107]. Those drawbacks can be neglected by developing circuits focusing on self-compensating means, e.g., relying on pairs of transistors rather than single elements [107].

6.3. Medical Related Applications

FHE-based devices are the groundbreaking next step in developing a new class of medical instruments that are smaller, more compact, and more accessible in everyday life. Researchers have already found niches where introducing new flexible and packed construction could show its benefits over bulky and heavy construction [108–110].

6.4. Performing Electrode-Based Medical Investigation

One of the development fields where flexible devices have found their place is health monitoring in real-time. Depending on the disease diagnosis, the equipment could consist of additional elements like electrodes (for methods like ECG or EMG) or physicochemical sensors (analyzing bodily fluids and the physical environment of a patient). Solutions take various forms, most often attached to the examined body parts. An example of such an appliance could be dysphagia monitoring system [111]. *Dysphagia* is a medical term describing difficulties in swallowing caused by a broad spectrum of diseases. Nevertheless, the proposed method is shown in **Figure 2b**. The system took the form of a patch attached to the bottom side of a jaw and monitored muscle activity in the region by utilizing EMG electrodes to collect signals captured in **Figure 2c**. The solution communicates with a computer that performs measurements and processes incoming signals, creating a usable rehabilitation platform shown in **Figure 2a**.

Another illustration of fresh air brought by FHE technology is a body-attachable ECG module utilizing soft and hard electronics (including unflexible elements) and integrating electrodes with the necessary equipment (like an analog front-end, Bluetooth SoC for data acquisition, and a small coin cell battery holder) on one Kapton substrate. Besides ECG possibilities, the device beholds a skin temperature monitoring system. One of the usages foreseen by research was monitoring of physiological response (focusing on cardiac reaction) during physical activity [113].

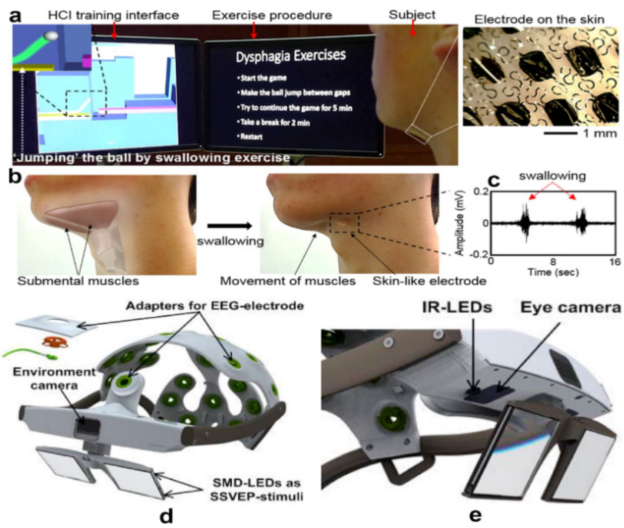

Figure 2. Overview of the proposed rehabilitation system integrating EMG and BCI control for swallowing and eye movement detection. The system includes a sensor-based EMG interface for swallow-related exercises and a BCI headset for eye movement control. Reprinted with permission under the Creative Commons Attribution 4.0 International License [111]; (a) The rehabilitation system setup featuring EMG-based ball control for interactive therapy. (b) Flexible EMG sensor placed on the chin capturing muscle movement. (c) Sample EMG signal collected during swallowing using the chin-mounted sensor. (d) BCI headset used for eye movement detection. (e) Eye movement control interface integrated with the BCI system. Subfigures (a)–(c) reprinted from [111]; subfigures (d)–(e) reprinted from [112].

6.5. Analysis of Bodily Fluids and Patient's Environment

The presence of new space-saving devices attached to a body gives medicine a new opportunity to expand its area of health investigation. One of the noted fields is bodily fluid analysis, especially sweat. The proposed solution comprises a network of various electrochemical sensors connected with a flexible data processing module. The analysis covers quantities like skin, temperature, electrolyte content, and the presence of substances like glucose or lactic acid [114].

6.6. Measurements of the Surrounding Environment and Estimating Its Health Impact

Another usage of novelty was found in the prevention of damage caused by pressure ulcers. Pressure ulcers are created under certain conditions of long-term cut-off of blood flow in specific parts of the skin. Before, medicine did not develop an efficient solution for risk estimation and early detection of them. The presented appliance relies on the principal method of impedance spectroscopy, which utilizes a network of sensors attached to the skin. The network is connected to an external circuit, performing impedance measurements and presenting a result as heatmap presenting the damaged area for analysis by a *physician* [115].

6.7. New Human-Machine Interfaces

Recent years have shown us new possibilities for interacting with machines, including methods relying on bioindicators like ECG, EMG, or brain activity. One example of such a system is a sensor system emerging electromyography electrode controlling physiological muscle response [116–119], creating an HMI interface with a sensorimotor prosthetic. The suggested solution was presented in the form of a multilayer skin patch serving as a sensor frontend for the machinery providing prosthetics control. Patch as such, provided strain sensor, EMG electrodes, and temperature sensor functionality, which together can be translated into sensorimotor commands for prosthetics [112,117,119].

It is worth mentioning the subcategory of HMIs called Brain Computer Interfaces (BCI). The implementation, shown in **Figure 2e**, contains 22 EEG electrodes connected with two eye-tracking cameras. **Figure 2e** shows a little bit more information about the implemented eye-tracking system, highlighting the position of crucial components. Complex information collected from different brain regions combined with eye movement data can be processed by adaptive signal processing algorithms fitted to a mental state and image recognition algorithms [112]. The solution is a great example device utilizing flexible FHE with potential usage by disability affected people with no capabilities to manipulate external objects or with limited communicational abilities due to, e.g., paralysis.

7. Social Media and Websites

As a rapidly growing technology, the Internet has answered numerous issues, including those connected to healthcare. According to research carried out in 2014 among Americans, 72% of adult Internet users had searched online for information about different health conditions [120]. Nowadays, in the era of social media, access to medicine-related content is even easier. We are provided with real-time, free-of-charge data, with the possibility of personal communication and exchanging experiences [121]. However, the quality of information may differ significantly from various levels of impact to different quality and reliability [122].

7.1. Raising Awareness

We can observe a strong impact of the Internet on people's knowledge of healthcare. Most first-time pregnant women use online websites and dedicated apps, and most consider these information sources about pregnancy reliable [123]. A relationship has been observed between social media campaigns and positive change in behavior during the COVID-19 pandemic [124]. It was also used to share personal stories of healthcare workers fighting the coronavirus, who helped spread the knowledge in that difficult time [125]. Internet campaigns on mental health seem to educate and reduce stigma successfully [126].

7.2. Providing Accessibility

Social media make the world more accessible. For example, it helps people with disabilities to be active by giving them access to information, including education, and enabling online interactions [127]. As patients share real-life experiences on social media platforms, their accounts provide valuable information for a deeper understanding of their conditions [128]. It is also a helpful tool in marketing healthcare services: it includes information about medical facilities and feedback from their clients [129]. To ensure that the information flow is consistent, hospitals have websites designed for patients and workers [130]. The Internet has become another workplace for doctors –it allows for online consultation– a time and money-saving alternative for conventional appointments [131].

7.3. Healthcare on Popular Platforms

Facebook, Instagram, YouTube, and TikTok are among the most popular social media platforms. **Table 4** shows examples of activities in the area of healthcare [132–138].

7.4. Benefits and Potential Risks

Besides many benefits, using social media and websites in healthcare is connected to several risks. They are listed in **Table 5** [127–131,139–142], which shows the advantages and disadvantages of the discussed solutions.

Current AI models do not always interpret the data correctly, so medical chatbots are unreliable and need additional training to provide correct advice (although they can have accuracy above 50%) [140]. Moreover, due to the lack of standardization and general indicators prepared to compare chatbots, the development of this technology may be slower than needed [143].

Despite raising awareness, social media can harm mental health, especially among young users, who are considered an active group [141]. Unfortunately, research in this field faces difficulties, such as missing data, because the platforms are not eager to share information with scientists [144].

Another problem is misinformation, which primarily affects people with limited access to valuable medical information [142]. It has become a priority in online healthcare information to detect and fight unreliable data, so there is a growing interest in creating applications to deal with this issue [145].

Table 4. Examples of Actions on Social Media Platforms in the Area of Healthcare [132–138].

Platform	Actions
Facebook	Parental groups as a place for support and discussions about children's conditions [132] Facebook advertisements on healthcare in political campaigns [133]
Instagram	Healthcare influencers advertising healthy lifestyles among young people [134] Educating patients with high risk of cancer by gynecology oncology providers [135]
Youtube	Educational videos both for patients and doctors [136]
TikTok	Videos created by healthcare workers [137] Sharing experience of studying medical-related fields [138]

Table 5. Advantages and Disadvantages of Social Media and Websites in Medicine [127–131,139–142].

Advantages	Disadvantages
Effective healthcare marketing [129]	The issue of security of patients' sensitive data [139]
Access for disabled people [127]	Not mobile-friendly websites, accessibility errors [130]
Contact with professionals online [131]	Inaccuracy of AI models [140]
Providing information about the real-life experience of patients [128]	Adverse effects on mental health [141]
Digital systems for hospitals [130]	Spreading misinformation [142]

8. Electronic Drug Delivery Systems

The usage of electronics in medical applications has significantly increased in the past decade. Electronic drug delivery (E-DD) is, without a doubt, a perfect example of it. It is widely used to monitor and track various therapies, from managing diabetes to treating epilepsy [146]. It might sound like a new concept, but E-DD's first applications and importance were noticed around 40 years ago [147]. The reason behind the ongoing development of those systems is a patient's appetite for greater functionality and the simplicity of daily drug dosage. During studies in the early 2000s on compliance with prescriptions and doctor's recommendations, a significant correlation was shown between conscientious adherence to therapy and improved health among patients on long-term therapies [148].

8.1. Forms of Electronic Drug Delivery Systems

There are several ways of delivering drugs to the human body. All of them are equally important due to their use in different cases, depending on the patient's requirements. Electronic transdermal patches deliver medication through the skin, ensuring controlled and continuous drug administration for conditions like motion sickness, cardiovascular disease, chronic pain, and smoking cessation. This method maintains steady drug levels and eliminates pulsatile entry into the systemic circulation [149]. Recently, electronic ion pumps that deliver ions and charge drugs from the source electrolyte have developed a lot. They are electrophoretic delivery devices transporting charged species through ion exchange membranes, offering high resolution and dosage precision without liquid flow. This technology shows promise in addressing therapeutic challenges, demonstrating efficacy in triggering cell signaling, halting epileptiform activity, influencing sensory function, managing pain, and even affecting plant growth through phytohormone delivery [150]. Another critical topic is the delivery of drugs by microchip devices. Microelectromechanical system-based devices can store drugs in their most stable form and release multiple medications at precise times by selectively opening various reservoirs as needed for each drug dosage [151]. Worth mentioning are also auto-injectors commonly mistaken for "pens" used for diabetes treatment. They automatically insert prefilled syringes, which is incredibly convenient for patients with the daily requirements for drug delivery [152]. Electronic capsules with pH and temperature sensors are the last form of delivering drugs to the organism.

8.2. EDD Application in Diabetes and Epilepsy Treatment

It is safe to assume that progress in electronic drug delivery systems, which led to better adherence to therapies, was inevitable, and these days, it is noticeable. For example, futuristic insulin pens for the level of glucose in blood measurements that could transfer data via Bluetooth, like Contour Next One or OneTouch Veiro Flex, are already being replaced by noninvasive Dexcom systems with real-time glucose readings [153]. The United States Food and Drug Administration (USA FDA) approved the Dexcom G6 system in March 2018 due to its precise measurements. It worked so well that in February 2023, the company released a new G7 generation with even more ease of use and exceptional accuracy. EDD development in past years has also affected the treatment of epilepsy by reducing the use of main therapeutic approaches to this disease, which had low efficacy and potential side effects. Instead, research was started by the Key Laboratory of Neuropharmacology and Translational Medicine of Zhejiang Province on the delivery of antiepileptic drugs (AED) with nanoengineered drug delivery systems using hybrid nanoparticles [154]. Its main goal is to release drugs on demand to suppress epileptic discharges and properly penetrate the blood-brain barrier, which would prevent side effects of treatment. It is a massive breakthrough for patients during status epilepticus treatment, which requires regular administration of medications to control their repetitive seizures. For them, the inability to control status epilepticus may be associated with severe neurological sequelae and a short-term mortality of 15 to 20% [154].

8.3. Digitalized Health with Personalized Drug Delivery Systems

With various apps, smartwatches, or other healthcare Internet of Things devices, delivering proper doses of drugs at appropriate times of the day is becoming as efficient as possible. Some private clinics have already launched their apps to make appointments, chat with doctors, store medical referrals for examinations, and, most notably for us in this article, they store drug prescriptions with their exact instructions. An example might be Polish LUX Med, the leader in private healthcare, which has more than 1 million downloads of its app in the Google Play Store. Managing chronic conditions like heart disease, diabetes, and brain disorders presents challenges. Treatment often involves multiple doses based on severity, lifestyle, other medications, and age-specific needs for children and the elderly [155]. Due to flexible on-demand doses, personalized and digitalized drug delivery systems allow for optimal health outcomes. Even if most medical professionals would never recommend "googling" symptoms and instead visit a clinic, most people have easier access to the internet than medical healthcare, and some people even have no access to medical healthcare. According to a 2019 report, there are over 1 billion health-related searches every day [156]. Of course, people need to filter information to avoid misinformation, but overall, people are more informed than ever thanks to digitalization.

8.4. Artificial Intelligence (AI) and Machine Learning (ML) Algorithms in Electronic Drug Delivery

In recent years, integrating AI and ML technologies with electronic drug delivery systems has reshaped personalized medicine. The terms mentioned above were extensively detailed in the "Artificial Intelligence (AI)" section of this revision paper. In this paragraph, I would like to highlight their specific applications in electronic drug delivery systems. By drawing from extensive patient data, including physiological parameters, medical histories, and real-time feedback from wearable devices, AI algorithms are now proficient at tailoring drug dosages and schedules to meet each individual's needs. These advanced systems ensure precise medication delivery and adapt treatment plans in real-time based on patient health changes or medication effectiveness. Additionally, AI-driven EDD platforms offer valuable insights into patient adherence and treatment outcomes, empowering healthcare providers to optimize care strategies and improve patient well-being.

9. Conclusion

This paper presented a comprehensive review of the latest developments in electronic and digital technologies applied to the medical and healthcare fields. Topics explored include wearable devices, the Medical Internet of Things (M-IoT), EHR systems, smartphone applications, AI, flexible electronics, digital healthcare during COVID-19, medical sensors, social media, blockchain, Nano-BioElectronics, and robotic surgery. By offering comparative analyses of technologies—such as the use of blockchain in data management and robotic surgery techniques—this paper provides valuable insights into their respective strengths and challenges. The findings underscore the growing importance of digital and electronic solutions in transforming healthcare delivery, improving patient care, and addressing emerging global health challenges. This review not only consolidates current knowledge but also identifies future directions and gaps, offering a useful reference for researchers, practitioners, and policymakers in the field.

Author Contributions

Conceptualization, A.S.S.A., A.K., M.J., P.K., K.T., P.T.; methodology, A.S.S.A., A.K., M.J., P.K., K.T., P.T.; software, A.S.S.A., A.K., M.J., P.K., K.T., P.T.; validation, A.S.S.A., A.K., M.J., P.K., K.T., P.T.; formal analysis, A.S.S.A., A.K., M.J., P.K., K.T., P.T.; investigation, A.S.S.A., A.K., M.J., P.K., K.T., P.T.; resources, A.S.S.A., A.K., M.J., P.K., K.T., P.T.; data curation, A.S.S.A., A.K., M.J., P.K., K.T., P.T.; writing—original draft preparation, A.S.S.A., A.K., M.J., P.K., K.T., P.T.; writing—review and editing, A.S.S.A.; visualization, A.S.S.A., A.K., M.J., P.K., K.T., P.T.; supervision, A.S.S.A.; project administration, A.S.S.A., A.K., M.J., P.K., K.T., P.T.; All authors have read and agreed to the published version of the manuscript.

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The authors declare no conflict of interest.

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