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Survey paper

A Survey on Wearable Technology: History, State-of-the-Art and Current Challenges

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ABSTRACT

Technology is continually undergoing a constituent development caused by the appearance of billions new interconnected "things" and their entrenchment in our daily lives. One of the underlying versatile technologies, namely wearables, is able to capture rich contextual information produced by such devices and use it to deliver a legitimately personalized experience. The main aim of this paper is to shed light on the history of wearable devices and provide a state-of-the-art review on the wearable market. Moreover, the paper provides an extensive and diverse classification of wearables, based on various factors, a discussion on wireless communication technologies, architectures, data processing aspects, and market status, as well as a variety of other actual information on wearable technology. Finally, the survey highlights the critical challenges and existing/future solutions.

1. Introduction

Today, the rapid proliferation of the Information and Communications Technology (ICT) niche is being pushed by an increasing number of new services and growing user demands. Generally, the number of interconnected handheld devices has been growing tremendously from year to year, empowered by both consumers and broad penetration of the Internet of Things (IoT) [1]. Small, affordable, and very different in shape, purpose, and application, the IoT devices had a tremendous impact on the development of the telecommunications field, not only bringing new long-range wireless technologies to the market, defining new requirements in terms of reliability and availability but also pushing network operators and vendors to redesign the entire ecosystem, switching from conventional human-generated traffics to more diverse IoT one.

This tremendous impact on the ICT domain and proliferation of the IoT allowed the developers to bring their attention to an entirely new market segment – a separate niche requiring standalone efforts has emerged as devices carried by humans but no necessarily generating the human-type data. Internet of Wearable Things (IoWT) has emerged as part of a broader IoT, bringing new challenges from various technological perspectives to the research community [2].

The terms *wearables*, *wearable devices*, or also *wearable technology* refer to small electronic and mobile devices, or computers with wireless communications capability that are incorporated into gadgets, accessories, or clothes, which can be worn on the human body, or even invasive versions such as micro-chips or smart tattoos [3]. Compared to today's smartphones and tablets, the primary added value is that wearables can provide various monitoring and scanning features, including biofeedback or other sensory physiological functions such as biometry-related ones [4]. Wearables can continuously measure such values —

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Fig. 1. Perspective on the development of personal wearable ecosystems.

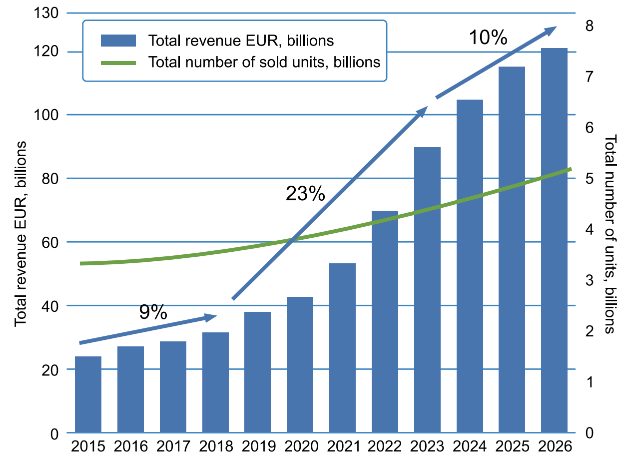

Fig. 2. Wearable market growth forecast [9].

restricted by their battery constraints; they are convenient, seamless, portable, and can offer hands-free access to electronics.

The consumer-wearable devices of today are beyond their inception but still very much in their infancy. Most people still use a combination of an activity tracker and a smartphone, see Fig. 1, limiting their experience to the number of steps and heart rate. Indeed, the variety of data collected and processed in a wearable ecosystem context can hand over an unprecedented user experience for humanity [5]. In addition to conventional sports trackers, smartwatches, on-body cameras, heart rate meters, and eye-wear, the upcoming generation of wearables will also involve augmented-, virtual-, mixed-, and enhanced-reality devices, various smart clothes, and industrial wearable equipment.

As foreseen by the ICT industry, almost 70% of early adopters have shown their interest in correlating their lives with the next-generation wearables [6]. Predominately, a significant portion of IoWT available on the market today already provides a smartphone-like experience by employing voice and gesture control together with well-designed input and output interfaces.

Nonetheless, the miniaturization trend, portability, wireless communication, energy-efficient computing, and advanced display technologies have been combined to create state-of-the-art smart devices. The patriarch of these devices, a smartphone, was released back in 1992 [7], and intelligent media are now ready to lead the next great wave of innovation. Comparing traditional smartphones with wearables, both have their pros and cons. A traditional smartphone's main advantage is its higher accuracy in various performance metrics due to less power consumption limitations as a general trade-off to size. On the other hand, wearables are highly battery-constrained devices, yet have the potential to change the world as we know it — just as mobile devices did over the past 20 years. It is expected that they will improve the technological and socio-cultural parts of our lives. Moreover, wearables also have the strength to improve well-established sectors, such as the smartphone industry and other hand-held devices. This trend is confirmed by many recent studies and will be discussed in this survey.

From the monetary perspective, the wearable market is anticipated to keep on growing exponentially in the coming years. The forecast is at more than 20% growth rate annually, and the market is expected to reach over 40 billion EUR per year in the next 5 years with more than 150 billion EUR by 2028 [8–10]. A recent number of wearable shipments, estimated at 113.2 million in 2017 with total market size of $70 billion in 2019, is forecast to reach 222.3 million deliveries yearly by 2021 [11,12]. Moreover, the outbreak of COVID-19 also made a tremendous impact on the wearable devices evolution driven by the implementation of various crowd-sensing and contact-tracing platforms [13–16]. The proliferation of wearables is thus expected to steadily increase over the following decades, with a predominant transition from bracelets and sport trackers to smarter and more feature-rich wearables. Wearable technology has a tremendous impact upon ICT industry, and smart wearables are expected to disrupt most personal and business sectors, such as the industrial, healthcare, and sports domains.

Moreover, the global enterprise wearable market alone accounted for over EUR 18 billion in 2017, and it is predicted to grow at a Compound Annual Growth Rate (CAGR) of 11.8% during the forecast period, 2019 – 2026 [17]. The details on market changes as well as future perspective [9] are given in Fig. 2. Here, wearable devices could be used to improve employees' physical activity, enable relaxation more effectively, and increase workers' safety and work efficiency [18]. Added value is also achieved in other sectors, such as smart city, transportation, gamification, and infotainment. Wearable technology relieves people from continuously having to hold their smartphones in their hands from the usability perspective. This convenience feature allows handling calls, emails, texts, and many other alerts without even getting the bulky devices out [19,20]. Following Llamas' work, "within the enterprise, wearables can help accelerate companies' digital transformation by transmitting information back and forth while allowing workers to complete their tasks faster" [21].

The mobile devices' market growth brings new and usable devices, numerous benefits, and new applications from the users' perspective. One of the primary stimuli brought by wearable technology is the encouragement of proactive solutions to deal with healthcare, fitness, aging, disabilities, education, transportation, enterprise, finance, entrance systems, gaming, music, and many others. Since wearables, as known today, were historically planned as purely medical devices, let us first consider an example from the healthcare field. Unfortunately, people tend to deal with potential health issues reactively, e.g., when they feel sick or in pain, they tend to appoint a visit to their doctor. Carrying a wearable device may potentially forecast the disease by continuous health tracking and even inform the doctor automatically in order to take measures to prevent the incipient threat actively [22]. Even the simple activity trackers are already capable of monitoring sleep patterns, heart rate, level of stress, or body temperature that could be utilized for improving the health habits of any individual [23].

Significantly, the shift toward advanced devices, such as Augmented Reality (AR)/Virtual reality (VR)/Mixed Reality (MR)/eXtended reality (XR) devices, low-end wearables, and other monitoring devices, together with a transition to Beyond Fifth Generation (beyond-5G) mobile networks would also bring several challenges for the device vendors, network operators, and end-users. In particular, those challenges are related to the paradigm shift from conventional Human-to-Human interaction (H2H) to more Machine Type Communications (MTC) interactions [24]. This segment brings completely different requirements, e.g., utterly different traffic patterns, higher reliability, lower latency, highly mobile scenarios, stringent security and privacy needs, and higher energy-efficiency demands than the H2H ones [25].

All of the conditions mentioned above lead to an indigenous increase in power consumption and the need to recharge the wearable/handheld devices daily, reducing their attractiveness and limiting the wearable applicability. Modern technologies, such as energy harvesting [26] and wireless charging [27], may assist in solving the energy bottleneck, but the corresponding impact on the user's health has not yet been studied in detail [28]. Besides, energy harvesting technologies are still far from mass adoption [29].

Overall, research in wearable technology is growing, which is demonstrated, among others, by the number of publications in the IoWT domain. Nevertheless, only one unified review is available to the research community. In contrast, others have a particular focus on some specific area (eHealth, sensors, adoption, etc.), while this paper attempts to synthesize a standalone executive summary of various technological aspects as well as related challenges. As of February 2021, the authors identified the following papers related to our survey, i.e., at a comparable level of abstraction and topics' coverage.

Several works have already reviewed materials, technologies, and applications involving Wearable devices. One of the broadest and detailed surveys was shown to the IEEE community in 2017 [30]. According to the authors, the paper has a *product survey* style and is mainly focused on the market-available wearable accessories, eTextile and ePatches classification, and computing-, energy specifics, and security aspects with a focus on present technologies. To note, close to half of the paper deals only with the classification of wearable devices available in 2017. A very recent review on wearable technology and consumer interaction [31] introduced five main themes, including decision-making, well-being; consumer behavior; utilities; and Big Data analytics. Above all, they showed the lack of integration within wearable technologies, which is driving to fragmentation, disconnected terminologies, and studies that are not based on appropriate results.

The review performed by Xue et al. [32] introduced issues about technologies, users, and activities with intelligent wearables. Moreover, it identified the main risks (privacy, safety, performance, social and psychological) involving wearables, which were also mentioned as hot topics/themes for wearables in other related reviews [33]. The analysis introduced in [34] focused on the current research highlights based on nanomaterials and evaluated the electronics under the perspective of actuators and sensors. The applications of Wearable Sensors were analyzed for healthcare and human movement monitoring. In contrast, the review introduced in [35] targeted the evaluation/assessment of physical activity apps and wearables. They identified that 75 out of 111 analyzed works used in-device sensors to measure physical activity.

Numerous works specifically target the eHealth segment, e.g., the work [36] dated 2015 provides an extensive overview of wearable health-monitoring systems and related communication aspects sensors and related implementation challenges. Another relevant work [37] also covers the communication and architectural aspect of the eHealth domain, extending [36]. Both are, however, strictly limited to this particular segment. A cross-section of technologies for Sports and e-Health was also assessed in [38]. The primary purpose was to evaluate their reliability and suitability. They detected that most of the analyzed technologies were not formally validated by an independent actor, and only 5% provided a formal validation. The highlights provided in [39] included the rising of wearables and the future for monitoring human activity as well as biological signals.

Different from the other works, this paper provides a synergy of various aspects of wearable devices from perspectives of communications, computing, localization, modern and future communication capabilities and identifies challenges for each of the directions. As such, it provides a standalone dataset of devices up until 2020, discussing the aforementioned aspects without losing itself in (unnecessary) technical details or device classification, as in [30].

In line with the discussions so far, the main goals of this paper are:

- G1. To provide a detailed historical overview of wearable technology evolution;
- G2. To highlight the state-of-the-art in the field of wearable technology, including mass-consumer perspective, main architectures, market-available devices, and related technical classifications;
- G3. To identify open challenges and provide a vision of future developments related to wearable markets and wearable computing.

The rest of the paper is structured as follows. Section 2 provides a detailed insight into the history and development of wearables from the early 13th century till nowadays. Section 3 addresses the state-of-the-art of wearable-technology evolution and outlines the main classification, architectures, communication possibilities, and data processing aspects of modern wearable devices followed by the main trends in active wearable-technology development from both industrial and academic perspectives. Section 4 contributes by providing the list of main open challenges and future perspectives. Section 5 concludes the paper with a discussion summarizing the main findings of this work. The appendix provides the results of the comprehensive market analysis reflecting various types and models of wearable devices being currently available on the market and under research.

2. Historical perspective on wearables

The wearables we know today are mostly treated as smart-by-definition devices. People tend to forget that "smartness" has not always been defined by processing the data on a chip, but rather by delivering a better experience for actual users. The next subsections give an overview of wearables' evolution from the 13th century to 2015. The evolution is also graphically depicted in Fig. 3 for the ease of perception.

2.1. Before the 20th century

The journey of wearables started with the invention of spectacles around the 13th century by English friar Roger Bacon, who was based in Paris and outlined the scientific principles behind the use of corrective lenses in his Opus Majus (c.1266) [40]. Before R. Bacon, there had been mentions of presbyopic monks using segments of glass spheres that could be laid against reading material to magnify the letters (i.e., a magnifying glass called "reading stone"), but those are more questionable in terms of actual *wearability*. Glasses by Bacon were the first wearables designed to be seamlessly carried and improving the vision, thus, becoming the pioneering smart glasses [41].

The first pocket mechanical watch, possible to be carried around, dates back to the beginning of the 16th century, and it is believed to be the Pomander (Bisamapfeluhr in German) watch [42]. Peter Henlein made it in 1505 as a portable but a not-very-precise clock. This design started a hype in wearable watch development, followed by more than ten different models in the next one hundred years [43]. Later on, pocket watches have also been developed significantly with the evolution of miniaturization [44], which led to the idea of strapping the device to the wrist in the 19th century. Military needs primarily drove the developments at that time [45].

From the smart ring's perspective, the first known one is Abacus Ring from the early 17th century during the Qing Dynasty era [46]. Back then, a standard abacus was combined of 10 parallel wires located between two boards on a frame with nine beads on each of them. It was specially designed to be a compact smart accessory used to help traders. It led the way towards modern wearable computers and, at the same time, towards modern smart rings [47].

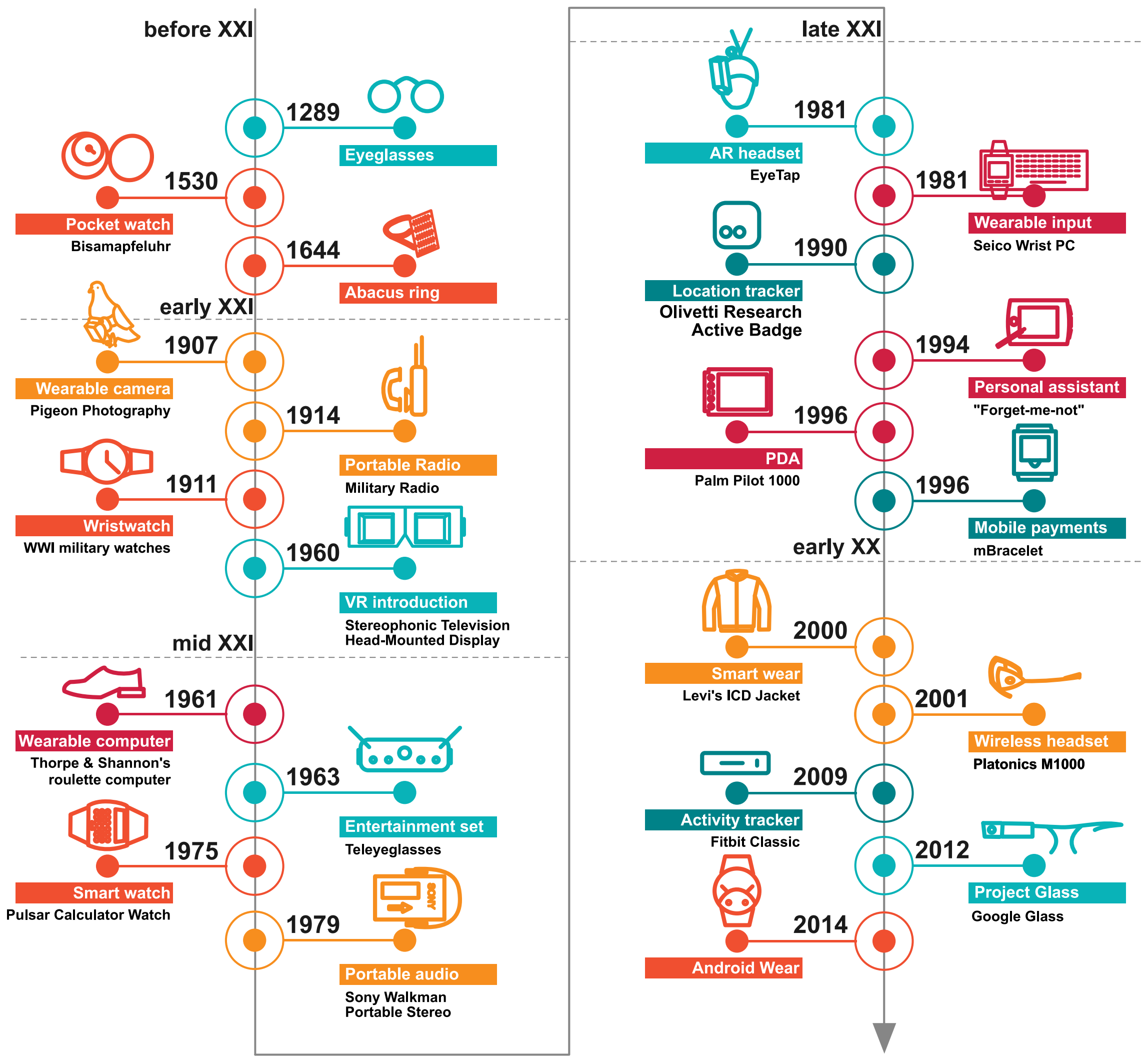

Fig. 3. Milestones of the wearable devices evolution.

2.2. *Early 20th century*

The first step from the portable cameras' perspective is the Pidgeon camera, developed by the German inventor Julius Neubronner in 1907 [48]. Unlike many other technological breakthroughs of those times, the camera was designed to record Neubronner's pigeon flights, while this invention is sometimes mistakenly referred to as based on military demands. It is probably because pigeon photography was widely used during the first world war for aerial surveillance together with airplanes [49].

Indeed, wearable development driven by the military during the World War I-II period was enormous. In the first place, the first carried-on wireless systems were redesigned for field communications [50]. Those were very bulky and, at first, used to be carried by cavalry horses. A breakthrough in portable radio has been a "packset" system, which later became known as a "walkie-talkie", developed in 1937 by Donald Hings [51].

Wristwatches were necessary for the planning and coordination of various operations, thus, enabling the mass adoption of wearables in the prestigious military area [52] and, thus, allowing the marketing teams to adopt wristwatches globally. Simultaneously, the first wired hands-free devices integrated with flight helmets were being developed for navy and pilots [53].

After World War II recovery, the next big step in the development of wearable technology has been towards the VR by Morton Heilig, who patented "Stereophonic Television Head-Mounted Display" in 1960 [54]. It was soon followed by another patent of the "Sensorama Simulator" being an upgraded version of the initial device [55]. The device was indeed the first VR simulator with a binocular display, vibrating seat, stereophonic speakers, cold air blower, and an odors generator [56].

2.3. *Mid 20th century*

In 1961, MIT researchers Edward O. Thorpe and Claude Shannon concealed a timing device in a shoe that could accurately predict the ball's landing place on a roulette table. That became the first wearable computer hidden in the shoe [57]. The real story behind the invention was published later, in 1998 [58].

Just a few years later, Hugo Gernsback invented the TV glasses [59]. Those glasses weighed around 140 grams and were built around two battery-powered cathode-ray tubes allowing for the stereoscopic experience [60], which was a breakthrough for 1963.

Next, in 1968, Ivan Sutherland created the "Sword of Damocles" – known to be the first VR Head-Mounted Display (HMD) system, enabling users to immerse themselves in a 3-dimensional environment [61]. The development has taken almost ten years while the prototype was partially see-through and allowing head tracking.

Inspired by Edward O. Thorpe, Alan Lewis invented the digital camera-case computer to predict roulette wheels in 1972 [62]. Following Thorpe's approach, he used a radio connection between the recipient of the information and the person. The recipient used a computer to predict the roulette wheel and whispered the prediction via a radio link to the hearing aid radio receiver.

A significant breakthrough in the development of smartwatches was the appearance of the Pulsar Calculator Watch in 1975 [63]. The first-ever market-produced calculator watch was retailed at a price as high as $\$3,950$.

In 1977, Hewlett Packard released its first algebraic calculator watch [64]. The HP-01 was a genius of miniature and smart design with 28 keys on the clock display. Four keys are raised for ease of use (amount, alarm, memory, and time), and two were embedded, but one could still use them using the fingers [65]. The rest of the keys were important to press with a pen that instantly snaps the bracelet into the clasp. The cheaper versions, mainly produced by CASIO, still ensure the clock design of the calculator.

During the same year, the first camera-to-tactile vest was designed by the company "Smith-Kettlewell" for the blind in 1977. It took a decade of research. The device used a head-mounted camera to create a tactile representation on 10 inches and 1024 points grid located on the person's vest [66].

The mid-20th century period could be concluded by one more breakthrough in wearable devices – Portable Stereo Sony Walkman was released in 1979 as the first commercially available portable personal stereo cassette player with earphones [67]. Although it had two jack outputs allowing for privacy, it was the first luxury wearable with a leather case and stylish design.

2.4. Late 20th century

The wearable development in the 80s passed relatively fast, mainly driven by improving existing technology from previous years and a new AR wave. In 1981, Steve Mann had formalized the EyeTap project and developed the first backpack-like computer designed to process the data from a next-to-eye-mounted camera and showed it on the screen in front of an eye [68]. That was the first step toward modern AR glasses and the ancestor of Google Glasses [69].

The next massive acceleration of wearable computing development was Seiko's UC 200 WRIST PC introduction in 1981 [70]. It had 2 kB of storage and offered the possibility to spell the time and calculation. Despite that, a separate dock station and keyboard were available for purchase.

Nelsonic Space Attacker Watch pioneered a new niche of portable gaming in 1981 [71]. The watch was equipped with two buttons allowing playing popular arcade games anywhere and anytime. After one year, Nelsonic released portable Pac-Man and, later on, Super Mario Brothers.

The second big father of Google Glass is the Private Eye head-mounted display developed and sold by Reflection Technology in 1989 [72]. It had a monochrome monitor with a futuristic 720×280 resolution for that time.

The beginning of the 90s was lightened by creating The Active Badge, the first portable indoor location tracker in 1990 [73,74]. It was made by Olivetti Research and was suitable to transmit unique Identifiable Infrared (IR) signals to communicate a person's location, which could be treated as the birth of the Smart Room concept.

Since the technological development pace was only increasing, Hip-PC debuted by Doug Platt as a shoebox-sized computer just one year later [75]. It was based on Ampro "Little Board" Extended Technology module and, together with Private Eye and keyboard, formed an Agenda palmtop. It already had a floppy drive and many additional extenders.

Two years later, the development of widely known Knowledge-based Augmented Reality for Maintenance Assistance (KARMA) has started at Columbia University [76]. The system was also utilizing the Private Eye for an overlay effect. This project's main goal was to wire-frame schematics and maintenance instructions on top of whatever was being maintained.

The first steps for personal and portable electronic assistants were made already in 1994. Mik Lamming and Mike Flynn developed "Forget-Me-Not", a continuous personal recording system [77]. It was a technology that recorded the interaction with people and stored this information in a database for future use.

In March 1996, Palm launched the first-ever made mass-produced personal digital assistant (PDA) – PalmPilot 1000 [78]. Being essentially a one-chip computer, it has 128 kB of Random-access memory (RAM) and up to 12 MB of storage. These devices received a 160×160 pixel screen plus a stylus-based text input.

The year 1998 could be called the beginning of the wearable payment epoch, currently present on Apple Watch and Android Wear. The enabling device was the mBracelet [79]. It was a wrist-wearable computer designed for financial transactions with Automated Teller Machine (ATM). It had three slots that could accept interchangeable iButton buttons. The connection between the mBracelet and the host was through a three-color Light-emitting diode (LED) grid. The mBracelet plug-in interface allowed users to exchange messages by cross-shaking hands.

2.5. Early 21st century

Levi's Industrial Clothing Division (ICD) Jacket led the beginning of the 21st century, designed by Massimo Osti in collaboration with Philips [80]. The jacket was made of technological material with an internal network designed to interconnect electronic gadgets. The development became revolutionary for its time and influenced the further development of brands such as Acronym and Ma.Strum.

The year 2001 is the most known for introducing the first Plantronics M1000 Wireless Headset, followed by the launch of the lightweight M1500 version [81]. It was a combination of an M1000 Bluetooth headset and an innovative Bluetooth mobile phone adapter that plugs directly into the headset jack, giving all mobile users Bluetooth headset freedom.

Fossil Wrist PDA met the market in 2003. Its development began in 1999 by Donald Brewer, who struggled to make the watch small enough for the first year of development. He started the discussions with Microsoft engineers looking for an over-the-wrist platform and concentrated on developing "Smart Personal Objects Technology" (SPOT watches) [82]. After the size has been reduced enough, the screen was attached. The first device had 2MB of memory, which was expanded to 8MB for the commercial release. The price at debut was $249 US.

In 2004, the first-ever GoPro camera met the world [83]. Nick Woodman founded the company after surfing in Australia at 2002. The first model was small, light, and waterproof while being AAA battery-powered.

Later in 2006, "Nike + iPod Sport Kit" was released [84]. It was a device that measures and records distance traveled, pace, and more. Nike+ consists of a small accelerometer installed or already built into shoes, which connects to a Nike+ Sportband receiver connected to Apple products.

Fitbit was founded in early 2007 by James Park and Eric Friedman [85,86]. In 2008, Fitbit Classic was the first wireless activity tracker that could synchronize data with the Internet and have the same data available on a mobile phone. He was also innovative in the sleek form factor.

In 2009, Samsung S9110 Smart Watch was released. The company continued Dick Tracy's idea with a two-band wrist radio [87]. It was a dual-band General Packet Radio Services (GPRS) phone with Exchange email support. Samsung S9110 Smart Watch was the first smartwatches that included a full-color touchscreen, Bluetooth connectivity, music player, and voice recognition feature [88].

In early 2012, Eric Migikovsky thought about a device that could display messages from selected smartphones (Android and Apple devices) after creating the company Inpulse (Allerta) [89]. The initial version of the watch was attractive by the bold and original design. Moreover, it was easy to read in daylight on the "smartwatch" [90]. The design was highly accepted by the Kickstarter community [91]. After a few generations of watches and its acquisition by Fitbit, Pebble was removed from the market, leaving the niche of e-paper display-based watches abandoned.

In April 2012, information about Project Glass appeared on the Google Plus social network. The first post of the account was about the project's goals: to build a portable computer that will help "explore and share the world". A video called Project Glass was attached to the post with the project [92]. Soon after Google showed the concept, people saw the glasses in real life. Google co-founders Sergey Brin and Larry Page put on glasses in late spring 2012. At the Google I/O event on June 27, 2012, Google showed technology in action to a public audience under the price of $1500 [93]. This milestone is the beginning of VR and AR mass adoption.

The year 2014 could be described as the period of personal activity trackers boom. As a continuation and improvement of Fitbit's story, the most advanced device of that time, Basis, differed from other fitness ranges by collecting data such as heart rate, calorie consumption by activity, several sleep stages, and sweating and skin temperature with Body IQ technology [94]. The market faced numerous projects, and the number of people wearing those went sky-high in just a few years [95].

A standalone invention of 2014 was Tommy Hilfiger's solar power jacket to charge the phone [96]. Solar batteries were sewn into the jacket, connected, in turn, to the battery, which was located in one of the front patch pockets. Two devices could be connected to the battery, for example, a mobile phone or a tablet. Moreover, solar panels could be easily detached.

The next breakthrough for end-users was later in 2014 by introducing Android Wear (currently known as Wear Operating System (OS)) [97]. This marked the time when the first industrial giant officially stepped into wearables. Wear OS was the first operating system specifically designed for wearable devices, particularly for smartwatches, and was the beginning of Google's move towards taking a vital position in the wearable market.

Pushed by the technological race, Apple released its first wearable, Apple Watch, in 2015. While Google was mainly aiming at the market, the Apple Watch story has a more tragic background [98]. Before 2011, Steve Jobs had long and unsuccessfully fought pancreatic cancer, and experienced the healthcare industry's imperfection in the United States firsthand. He saw how inconvenient it was for the nursing staff to communicate with patients, how difficult it was to monitor an outpatient's condition and retrospectively collect the necessary information about the time spent outside the hospital. It was then that Steve Jobs decided that medical care could be improved with technology, and Apple should solve the problem of collecting and structuring data. Existing activity trackers were not suitable for monitoring patient conditions daily. That is why Apple came up with the Watch. The integration with a powerful software and cloud platform was supposed to facilitate doctors' work. Sadly, Steve Jobs passed away four years before the device was released.

The evolution of wearable technology during the period from 2015 till now will be covered in the next section as a state-of-the-art and market overview.

3. State-of-the-art and related work on wearable technologies

This section overviews the current situation in the wearable technology development domain. First, it provides the primary classification types of wearable devices in Section 3.1 followed by the underlying architectures in Section 3.2. Further, we list the data processing and computing techniques in Section 3.3. The discussion on currently available and developing wearable communication technology is provided in Section 3.4. The inseparability aspects from the wearable technology perspective are highlighted in Section 3.6. Section 3.7 shows an actual review of the leading wearable technology research directions from both academia and industry. Finally, this section is concluded with a list of the main directions driven by the mass market.

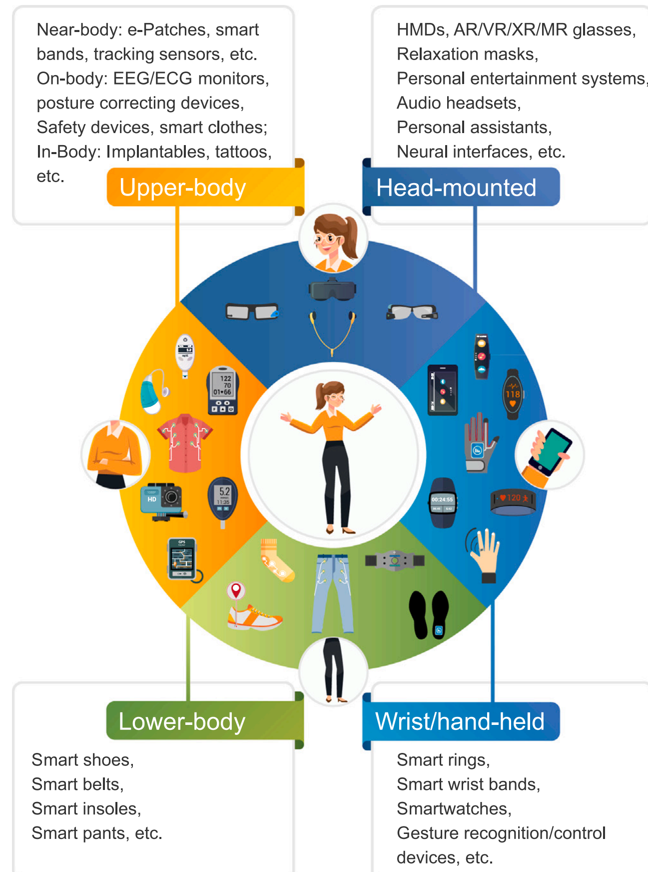

Fig. 4. Classification of wearable devices based on the on-body location.

3.1. Variety of wearable devices

Generally, the classification of wearable devices could be outlined from various perspectives based on various factors. Interestingly, devices worn and carried can have similar functionality but completely different form-factors, technology levels, different on-body locations, etc. Thus, the broadest classification is based on the application type, even though the other classification groups may significantly overlap.

One of the broadest classifications corresponds, but is not limited, to the following application/functionality types (discussed in more details in Section 3.7), and sorted alphabetically in Table 1.

Another significant factor for classification is related to the device type (without relation to the application area). The types are systematized in Table 2 and sorted alphabetically.

The variety of types could be broadened even further by decreasing the level of generalization. This subsection lists the main concepts present in the market and studied in the literature.

From the broad adoption perspective, the most intuitive consumer classification factor is related to the placement of the wearable on the human body. Here, the main groups (concerning device type) are, see Fig. 4:

- Head-mounted wearables: Those are mainly focused on perception and control aspects. The group related to vision covers: AR/VR/XR/MR glasses, relaxation masks as well as HMD and personal entertainment systems. Audio-related devices include headsets, personal assistants, bass systems. A standalone group is related to neural interfaces.
- Body-worn devices: Those have much broader functionality and could also be divided into the following subgroups:

Table 1
Classification based on the wearable application/functionality types (sorted alphabetically).

Type	Brief description
Communication functionality (C)	Provides the potential not to process the data locally but to exchange it with surrounding nodes and/or remote cloud.
Control/input functionality (CI)	A broad area of input devices ranging from smart buttons to sophisticated gesture recognition devices. This group's main task is to extend conventional Human-Computer Interaction (HCI) input focusing on the usability of the devices keeping a small form-factor as a rule.
Education and professional sports (ES)	Aim at improving the education and training by monitoring assistants.
Entertainment, gaming, and leisure functionality (E)	The improvement of the perception experience include, e.g., audio systems, personal entertainment displays, etc.
Heads-up, Hands-free Information (H)	Extend the conventional ways of the data delivery to the user utilizing personal assistants, AR, XR, Remote Expert Devices, wearable cameras, etc.
Healthcare/medical functionality (HM)	Separated from conventional sensing and monitoring ones due to the need to obtain medical device status that requires significant effort in the device development and testing as well as providing a high level of the obtained data trustability and the need for additional certification, however, covering similar devices, e.g., Electrocardiogram (ECG), Electroencephalogram (EEG) monitors, relaxation devices, neural interfaces, exoskeletons, etc.
Location tracking functionality (LT)	Requires to have either some Global Navigation Satellite System (GNSS) on board or, at least, a wireless communication technology. On the one hand, the concept here corresponds to location awareness from the node's perspective and, on the other hand, to remote localization of the device if needed.
Notification functionality (N)	Ranges from simple vibration notification to complex AR extensions. Similarly to sensing functionality, almost any personal device connected to the cloud directly or via the gateway can carry this functionality.
Output functionality (O)	Various visual, audio, or haptic-enabled devices to provide the user and/or people around with prompt information from the personal ecosystem.
Safety and Security functionality (S)	Personal safety devices, emergency assistants, etc.
Monitoring functionality (M)	Extremely straightforward and cheap to implement this functionality. Generally, any device that has an accelerometer on board can already provide some level of sensing. (Fitness and preventive healthcare — Activity Trackers, ECG, EEG monitors, etc.)
Wearable devices for pets and animals (PF)	Mainly covers smart collars, bark collars, smart clothes, etc.

  – Near-body and Sport: A segment for the devices supplementing existing wearable ecosystem, such as e-patches, smart bands, supplementary activity tracking sensors, etc.
  – On-body: EEG and ECG monitors, posture correcting devices, safety devices, various smart clothes, etc., form this subcategory.
  – In-body: The most significant niche from a medical perspective includes implantables, smart tattoos, etc.

- Lower-body devices: This group is still in the infancy but already includes some wearables such as smart shoes, belts, insoles, etc. Most of them carry specific monitoring functionality for professional sport or medical purposes.
- Wrist-worn and handheld wearables: Those are the most widely adopted and market-filled niche covering smart rings, wrist bands, smartwatches, gesture control devices beyond others.

The wearable-placement classification is one of the most natural ones. Designers, researchers, and early integrators should carefully consider that their device's placement is selected appropriately to fulfill the application requirements listed in the previous subsection.

In addition to the classifications mentioned earlier, wearables can also be classified based on their energy-consumption profile. Usually, devices with displays are comparatively more power-consuming than ones without a graphical output interface [2]. However, it also depends on the nature of the application and the extent of processing they perform. Therefore, wearables can be broadly classified into low, medium, and high-power wearables.

- Low-power wearables are mostly devices involving low-power components with limited capabilities that need to operate for a longer time, mainly for data acquisition/sensing purposes. These may include different healthcare-related wearables requiring low data communication rates. For example, a smart ring for sensing human physiological parameters can be classified as a low-power wearable since it is a compact device with a small battery, radio, and a few sensors onboard [168].
- Medium-power wearables include devices that may have a small display with slightly higher capabilities than low-end wearables. They can also have multiple sensors on board with direct or indirect internet connectivity options demanding medium data rates. These devices include smartwatches, fitness trackers, and other gadgets for activity/gesture recognition applications for individual, commercial, and industrial purposes [169].
- High-power wearables include devices that are more power-hungry since they include heavy processing units demanding high data rates and large displays capable of performing different compute-intensive tasks such as real-time image/video processing, Machine Learning (ML), etc. Examples include various headsets, glasses, head-mounted cameras for video crowdsensing, and others [170–172].

Wearables could also be classified based on the type of battery they use. Currently, there exist three different types of Lithium batteries available to be used in wearables thanks to the lightweight and high-voltage characteristics of Lithium [173]. Lithium Coin, also known as button cell batteries, are one of the earliest batteries developed for wearables such as watches, remote controls, etc. They are lightweight, low cost, and compact in design, mostly similar in size and shape to a coin. However, these were non-rechargeable and disposable batteries that needed to be replaced once depleted, which increases the e-waste problem [174]. Lithium-ion batteries are the most commonly used in wearables such as smartphones, smartwatches, fitness bands, etc. They are rechargeable, lightweight batteries with high-power density. However, the downside is that they are not very safe for wearables since these devices are in close contact with the human body. There have been instances where Lithium-ion batteries of smartphones have exploded due to overcharging/heating. They require special circuitry to ensure safe operating voltage and current. Moreover, their performance degrades over time, even if not used [173]. Lithium Polymer, also known as the Lithium-ion polymer, is rechargeable, lightweight, and comparatively safer than Lithium-ion. However, it is costly with a slightly lower power density than the Lithium-ion [175].

Table 2
Classification based on the wearable device type (sorted alphabetically and application types abbreviations are from Table 1).

Device	Refs.	Apps.	Power Prof.	Brief description
Activity trackers	[99,100]	C, H, LT, N, S, M, PP	L-M	Simple and relatively cheap devices mainly focus on everyday activity monitoring, including the number of steps, basic heart rate, and/or body temperature data collection. The main goal is to increase the overall physical activity participation of an average user.
AR devices	[101–104]	C, CI, ES, E, H, LT, N, OP	H	Augmented reality applications can provide additional "seeing with more eyes" information that cannot be displayed and is usually hidden from the observer in a see-through manner. The most attractive areas of the AR development are related to tourism, exhibitions, and manufacturing.
Audio systems	[105,106]	C, E, H, N, OP	M-H	Conventional wired and wireless headphones, bass systems, as well as hearing aids. Moreover, high-quality wearable audio could be integrated as part of XR or MR system to improve the immersion.
E-Skin (or nano patches)	[107–109]	C, CI, M, PP	L	An artificial skin with mechanical properties of human skin, providing various sensing functions with the main application area of artificial tactile systems. It is commonly located either right on the human skin or the arms of robotic systems to provide close-to-human perception abilities, e.g., to for the operation of humanoids.
E-Textiles (smart fabrics)	[110,111]	C, CI, ES, N, OP, M, PP	L-M	It is very similar to the e-Skin concept but broadens the opportunities to any close-to-the-body textiles that incorporate electronic functionality. Here, the sensors, circuits, or input/output devices are directly integrated with the fabric, allowing for seamless integration of the technology into everyday garments.
EEG and ECG belts	[112–114]	C, ES, M, PP	L-M	Allow monitoring the user's health state from both fitness, medical, and professional sports domains, potentially without the need for specialized medical equipment.
FPV, HMD	[115–117]	C, ES, E, H, N, OP	H	Devices for full immersion of, e.g., the Remote control (RC) of various robotic systems teleoperation, human interaction, e.g., police or firefighters, and/or conventional movie watching.
Haptic suits	[118–122]	C, CI, ES, E, H, N, M	H	Haptic feedback and capture both motion and biometrics features devices. Full or partial body haptic feedback systems are built into the suit and can be engaged in actions, on-demand, or in response to motion capture comparison to provide deeper immersion in various reality applications.
Ingestible and insertibles	[123,124]	C, M, PP	L-M	Objects that go in, through, and underneath the human body or may be a size of a medicine capsule and are packed with sensors, microprocessors, controllers, etc. Ingestibles are considered the next step of wearable technology and used in healthcare for disease diagnostics and monitoring.
Location tackers	[73,125]	C, ES, LT, N, S, M, PP	L-M	Functions of remote position estimation of the user. Those are of specific interest for pet owners and parents besides the historical crime-oriented market.
Neural interfaces	[126–130]	C, CI, H, N, OP, M, PP	M	Allow for a completely new experience in HCI for both complex medical states of the patients with movement disability, treatment of tactile function, behavior monitoring, and gaming.
Personal notification devices	[45,87,97,98]	C, H, LT, N, OP, S	L-M	Those could be considered as one of the earliest areas of mass wearable devices. When the first activity trackers received an embedded vibration motor and Bluetooth communications, it became possible to send a simple sign to the user about the incoming call or received message. Today, we cannot imagine almost any wrist-worn device without this function.
Portable Radio	[50–52]	C, CI, H, LT, N, OP, S	M-H	Those devices were also taking place in the wearable devices evolution back in the first part of the 19th century. Starting with walkie-talkies, we have arrived at the era when surviving a day without your smartphone could be problematic.
Relaxation masks	[131,132]	C, M	L-M	This group is an interesting set of devices that could be affiliated with luxury or medical purposes but keep the same function of improving the sleeping experience. The devices could also be suitable for people who travel a lot to improve the day-time adaptation period after, e.g., jet lag.
Safety buttons	[133,134]	C, CI, LT, N, S, M	L	This group corresponds to a specific set of notification devices but operating vise-versa, i.e., aiming to notify either some special units, e.g., police or hospital or the user's relatives, if something is happening with the owner.
Smart Bands	[135–138]	C, ES, H, LT, N, S, M, PP	L-M	Carry the functionality of modern activity trackers but sometimes also provide gesture recognition, stress/mood detection, or ECG monitoring functionality.
Smart clothes	[96,139–141]	C, CI, ES, E, H, LT, N, OP, S, M	M-H	A broad segment coupling together various common-looking clothes, ranging from pants to scarfs, but with invisibly embedded features, such as heating, charging, displaying, etc.
Smart contact lenses	[142,143]	OP	L	Devices to boost vision and monitor physiological parameters that help track blood glucose level from the body fluid, i.e., also tears intraocular pressure, with the help of the electronic device's resistance and capacitance.
Smart footwear	[144–146]	C, CI, ES, E, LT, M	L-M	Insoles, shoes, and socks are commonly used to monitor a person's posture, gait, a number of steps, beyond others, and are mainly utilized for training professional athletes from monitoring and stimulation perspectives and monitoring of children.
Smart gloves	[139,140,147–149]	C, ES, E, H, M	L-M	Another hand-held type of wearables is commonly utilized for systems requiring either sophisticated gesture recognition, rehabilitation, or providing better haptic feedback and other wearable devices.
Smart necklaces	[150–154]	C, LT, N, S, M	L-M	Luxury jewelry with activity tracking, health monitoring, posture correction, or safety functionality. This group of devices did not find much attention due to the actual need for miniaturization and keeping the appearance high.
Smart patches	[108,155–157]	C, M	L	Nodes consist of a peel-and-stick disposable part that is adhered to the skin and reusable sensor parts. Smart patches are easy to attach, maintain, and remove, acting as an example of Wireless Body Area Network (WBAN) system utilized in sports and healthcare monitoring.
Smart rings	[46,47]	C, CI, ES, E, H, LT, N, OP, S, M	L	Similar functionality as activity trackers but in a smaller form-factor and without displays. Some smart rings also have a notification device functionality but are kept in a fashionable accessorize form.

(*continued on next page*)

Table 2 (*continued*).

Device	Refs.	Apps.	Power Prof.	Brief description
Smart tattoo	[158,159]	C, ES, M	L	A set of biosensors implanted under the skin that measure glucose levels and change color depending on the result. Smart tattoos promise to make life easier for people with diabetes and become an alternative to permanent blood collection from the finger.
Smart watches	[45,97,160]	C, CI, ES, E, H, LT, N, OP, S, M	L-M	The most widely adopted wearables after the activity tracker. Generally, it provides almost the same functionality as a smartphone. However, most smartwatches' energy efficiency is still challenging without the gateway node due to the small form-factor.
VR/XR/ MR	[161–166]	C, ES, E, H, LT, N, OP, M	H	Visual immersion in the virtual environment with well-progressing VR applications being entertainment, education, and healthcare. MR are a particular subset of VR that involve merging the real world and the virtual world somewhere in a "continuity of virtuality" that augments completely real environments to virtual ones, as defined in the basic work. Interestingly, the relatively new concept XR is currently trying to unite all previously known reality-related paradigms.
Wearable cameras	[116,167]	C, LT, OP, M, PP	M-H	Devices are utilized by special units and athletes to record the environment for future analysis or via real-time streaming.

Indeed, the modern wearable electronics market is extensive, and, thus, the device classification approaches are also manifold. In this subsection, we have listed the most significant ones and also briefly highlighted less popular directions. The following sections provide more details on the devices' specifics and could also be considered an extension of the traditional classifications.

3.2. Architectural aspects

Typically, wearable devices use the owner's smartphone as a gateway to connect to the Internet. Therefore, operational efficiency may be limited if the gateway battery is empty or the connection options are insufficient. Currently, some wearable devices have a long-range wireless radio. However, continuous use is still not recommended due to high power consumption [2]. The evolution of wearable architectures is shown in Fig. 5.

Historically, legacy eHealth systems were based on a few specialized devices, such as biomedical sensors, worn by the patient, and on some storage and computation facility, either local or remotely located in the Internet [176] – the first architecture of wearable devices is a separate device. In such systems, wearables are allowed to monitor the users' status by collecting information ranging from physiological signals (e.g., heart rate, skin temperature, and physical activities) and their interaction with everyday objects.

At the next step of the architecture evolution, wearables became connected to more powerful external devices via wired links for data processing tasks that cannot be executed on the wearables due to their form factor limitation (Fig. 5A). Such architectures, mainly in healthcare-related applications, restrict user mobility, which is considered an obstacle to expanding wearable solutions. The key to smart healthcare services is the ability to track patients' health conditions without the need for frequent visits to medical centers or hospitals and provide real-time alerts in critical situations [177]. As a result, traditional wired health monitoring systems have been replaced with wireless wearable systems.

Due to the mass adoption of smartphones being a part of the personal wearable cloud, manufacturers started to aim at other consumer wearables as supplements in a personal ecosystem rather than standalone devices. It resulted in a new architecture where personal smartphones act as relays or gateways to transmit the data to the cloud either directly or with pre-processing in the custom applications. Furthermore, this architecture is supported by IoT technologies capable of bridging in the proximity of the users to a multitude of general-purpose smart devices. These IoT devices allow to gather further information concerning the environment surrounding the user and adapt it to the user's needs.

According to the IoT architecture provided in [178], the gateways are also called monitoring stations that are part of the perception layer for people with disabilities. Logically, with the development of personal wearable clouds, the logical star-like topology was supposed to join the communications (see Fig. 5B). However, due to the broad adoption

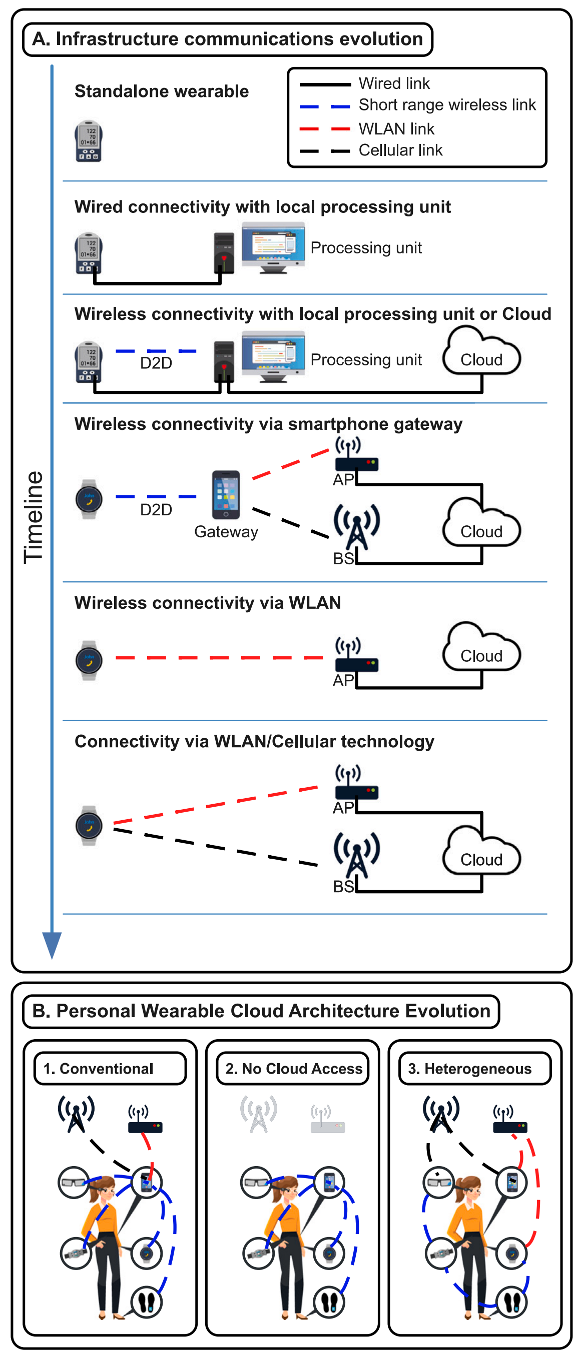

Fig. 5. The development of wearable architectures.

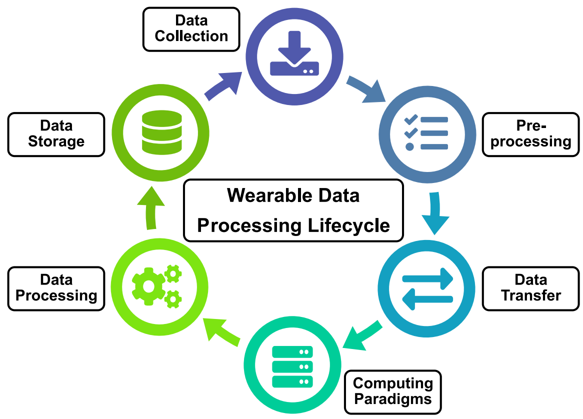

Fig. 6. Wearable data processing.

of Bluetooth technology as a leading connectivity enabler, wearable devices started to communicate purely in a centralized way using the gateway devices as masters.

Most fitness, sports, and healthcare wearable applications follow the fourth evolution step in Fig. 5A, while sharing their data with applications installed on the smartphones. This option implies several situations where wearables cannot connect to the network, such as the nonexistence of a smartphone nearby, non-installed applications on the smartphones, or an outdated phone software [179]. Considering such possible scenarios and the end-users ever-increasing expectations and needs, device manufacturers consider equipping wearables with short-range and long-range connectivity chipsets. As a result, these standalone wearables can function independently from other devices.

Although this standalone wearable-based architecture provides a way towards separating wearables from other personal devices and an opportunity to communicate directly with the cloud, it brings some challenges in terms of network design and dimensioning. For instance, additional loads on the wireless networks are expected due to the lack of pre-processing, usually performed by the gateway devices. Another challenge is related to the deployed communication technologies optimized for low-power operation, thus, long battery life and reduced device complexity.

Today, most wearable devices have at least two wireless interfaces on board. The trend of unifying the operation is expected to push vendors to add more wireless modules, with the possibility of intelligent technology selection mechanisms based on improved situational awareness.

3.3. Data processing

Wearable-based data are gathered and processed in large quantities depending on the individual product, yet it is always similar at its core. Fig. 6 depicts the basic cycle of wearable data. The individual stages of wearable data processing are characterized below before the details on the data transmission aspects.

3.3.1. Data collection

Wearable devices primarily collect and process user-generated data, and collective data collection is commonly referred to as crowdsourcing, a powerful tool for collaboratively retrieving a large amount of data. Crowdsensing is a way to enable the coordinated data gathering from the devices. There are three standard sensing techniques [180].

- *Participatory (active) sensing* refers to obtaining information through the user's action, such as measuring one's exercise on their smartwatch.
- *Opportunistic (passive) sensing* describes periodic action to gather information, determined by elapsed time, distance, or other metrics from the last data gathering.
- *Opportunistic mobile social networks* refer to self-organizing, point-to-point networks of devices sharing the information between themselves. The devices create the networks based on the vicinity to each other. Such networks can additionally assist other functions of the wearable, including positioning or user protection.

3.3.2. Pre-processing

Even though the central part of data processing takes place in different computing layers [181], sometimes minor filtering processes are executed in wearable and IoT devices. The early pre-processing stage is essential for wearable and IoT devices since they do not have enough computational and storage resources to process "unnecessary" data.

It is essential to highlight that the collected data contain incomplete and duplicate information, errors, inconsistencies, etc. It requires an early preparation before the data processing (locally or in the Cloud). Thus, once the data is collected, it should be filtered, structured, cleaned, and validated to improve the data's quality. As a result, the data processing step will take less time, and the output information will deliver better decisions.

During the data preparation, some steps take place to enhance the data and avoid unnecessary processing. For instance, gathering information is devoted to finding the most "representative" data from the collected set. It will be used throughout all the data processing. The cleaning and validation are then essential to detect the quality issues, including duplicate values, outliers, missing values, and inconsistencies. Once these issues are detected, multiple techniques can be used to remove missing values, delete outlier samples, merge duplicate data, etc.

3.3.3. Data transfer

The data transfer phase is an essential part of the wearable device data chain, and it is further discussed in detail in Section 3.4. At this point, we only note that many wearable solutions limit the amount of power spent during the data transmission by pre-processing it to decrease the actual amount. For example, it is achieved by applying compression schemes to the data before transmission [37]. Additionally, the power constraints usually limit the transmission's security, as proper data encryption is often computationally demanding.

3.3.4. Computing paradigms

Based on architectural development, it is reasonably straightforward to understand the specifics of wearable data processing. Computation and operation on bulky and raw data was a challenging task. Thus, during the firsts steps of the architectural evolution, wearables were mainly utilized as data collectors. For example, ECG monitors were given to patients for a few days to collect the data on the heart's rhythm and electrical activity. After that, the devices were connected to a personal computer with a wire for post-processing. This phase could be treated as the introduction of Multi-Access Edge Computing (formely Mobile Edge Computing) (MEC) for wearables, i.e., moving heavy computations to the closes network device instead of local computations.

With the smartphone's introduction as a gateway, wearable data processing on it was adopted swiftly. Following the vendors' footprints, most application developers aimed to save battery-constrained wearable lifetime by moving the smartphones' computations. The Edge operation hardened. Simultaneously, some AR/VR devices still do not have the required processing power or tend to overheat. Thus, the only option is to utilize a powerful Edge device for computing in trade-off to transmission overheads.

Today, wearable devices mainly follow Edge and Cloud computing paradigms, as well as Fog Computing [182,183]. The latter one is coined by CISCO in [184,185] and bridges the gap between the cloud and end-devices, allowing the computation, storing, networking, and data management near the target computationally-weak devices. In contrast to Edge computing, which handles data on a nearest network Edge node, Fog Computing processes data on a more powerful Fog node in a more general way, i.e., to equip the network Edge and network devices with virtualized services in terms of processing and storage along with offering network services. To this end, the Fog found little integration on wearables due to their proprietary communications/-computing nature and lack of knowledge about the devices in proximity and related communication aspects.

Cloud, Fog, and Edge computing are three levels that simplify IoWT. Nevertheless, there are many more paradigms suitable for the integration with wearables in reality [186], and the whole cloud system is much broader and more complex [187]. The actual classification also covers Mist Computing, Mobile Computing, Mobile Cloud Computing, Mobile ad hoc Cloud Computing, Multi-access Edge Computing, Cloudlet Computing, and Transparent Computing [188]. In this section, we overview these paradigms and explain their peculiarities from the wearable technology perspective, whereas the implementation challenges of computing paradigms will be discussed later in Section 4.

- *Mist Computing* is operating at the Edge of the network, usually consisting of energy-constrained microcontrollers and sensors. It is a network without data processing. In this case, the data is generated where it interacts with the physical world.
- *Mobile Computing* is a technology that allows transferring data, voice, and video through a computer or any other wireless device (e.g., wearable, mobile phone, laptop, tablets). Mobile computing is used to create context-sensitive applications (e.g., location-based reminders).
- *Mobile Cloud Computing* is a platform that brings together mobile devices and cloud computing and creates an infrastructure where both data storage and processing take place outside of a wearable device. It allows accessing the cloud remotely using a mobile device.
- *Mobile ad hoc Cloud Computing* refers to a group of mobile (wearable) devices in the proximity willing to share their resources, taking some incentives and collectively solving the task. It is usually deployed over mobile ad hoc networks and performs computation-intensive applications using other portable devices' resources in specific scenarios, such as natural disasters, sports broadcasts, etc.
- *Multi-access Edge Computing* (formerly Mobile Edge Computing) pushes the boundaries of Edge Computing by providing computing and storage resources next to low-power, low-resource mobile devices. It ensures connectivity and computing opportunities through wireless networks. In contrast, Edge Computing works solely between the mobile device and the closest powerful network node. This computing paradigm could be defined as an enabler for future wearable systems.
- *Cloudlet Computing* is an infrastructure that uses small data centers to move the functionality of the main data centers and bring the cloud closer to service consumers (being, essentially, wearables) [189]. Cloudlets represent virtual machine infrastructures that operators place between devices and the cloud. This paradigm is mainly focused on real-time applications for resource-constrained devices.

Indeed, the variety of options to efficiently execute computing between mobile nodes is vast.

3.3.5. Data processing

During the data processing phase, different techniques and methods are applied to the input data to obtain meaningful information. Nowadays, ML techniques are broadly applied to analyze and process the data, such as clustering, regression, classification, among others [190]. Additionally, these ML techniques can be run by using batch processing [191], real-time processing [192], and online processing [193].

Generally, the most significant part of the data collected by wearables are time series [194]. This kind of data could be typically used for classification purposes, anomaly detection, or forecasting. However, there are few obstacles connected to the analysis of time series. The main one is the limited amount of data, which can be dealt with using data augmentation techniques. The other issues are limited computation capacity together with limited power resources when the computations need to be done directly on the hardware.

Additionally, in the case of time series, other aspects should be considered, such as the occurrence of class imbalance and the possibility of multivariate time series. Unfortunately, the commonly applied method of augmentation could not be transferred from the image and speech domain into time series. This created demand to elaborate on the augmentation method for time series data [195]. The categories of the time series' augmentation techniques include six domains, i.e., time domain, frequency domain, decomposition-based methods, model-based methods, learning-based methods, and time–frequency domain.

The recorded time series gathered by wearables contain a special pattern, which indicates, for example, human behavior or physiological disturbances, potential pathologies. For creating a predictive model, it is necessary to use special ML techniques. Nonetheless, the preprocessing steps are also needed to obtain the final expected results. In terms of architectural choices, Convolutional Neural Network (CNN), Long Short-Term Memory (LSTM), Bidirectional Long Short-Term Memory (BLSTM), Multilayer Perceptron (MLP), Gated Recurrent Units (GRU), and transfer learning are robust in obtaining the state-of-the-art results for wearable data [196–199]. Additionally, the usage of classifier XGBoost was registered for the scalars' values [200]. However, it required earlier feature extraction steps. The LSTM and BLSTM architectures are suitable for this purpose because they can learn the long-term dependencies occurring in the signal [201,202]. 1D-CNN allows the algorithm to extract features and learn in time series what is expected for such purpose [203].

After the data processing stage, the useful information is exposed to the user through reports, graphics, tables, etc. It is then available for further storage, applications, and development.

3.3.6. Data storage

In this last step of data preparation, the altered data is stored for further analysis, which is then used by recommendation systems for marketing purposes and collective intelligence to improve the decision-making process.

3.4. Communication technologies

The wide range of wearable devices and related technologies allows for various supported connectivity solutions, defined by the wearable's requirements for range, data rate, power restrictions, mesh types, developer's preferences, and numerous other aspects. Data transfer specifics, including encryption level, coding and transmission schemes, modulation, and cyclic prefix, are also individually defined depending on the utilized technology. The most commonly used data transmission technologies in wearables include Near Field Communication (NFC), Bluetooth Low Energy (BLE), Wireless Fidelity (Wi-Fi), ZigBee, Low-Power Wide Area Network (protocols) (LPWAN), and other cellular or non-cellular IoT transmission technologies [204]. As illustrated in Fig. 5, both short-range and long-range communication technologies are being deployed in wearable networks. This subsection outlines the related communication technologies already available on modern wearables and promising candidates widely discussed to be integrated into the devices.

3.4.1. Short-range communication technologies

Generally, wearable devices can communicate with each other in a Peer-to-Peer (P2P) manner and with the gateway nodes using short-range technologies in mobile wearable networks.

Bluetooth (and its currently broadly adopted version BLE) is a short-range communication protocol for Personal Area Network (PAN) working at a maximum transmission distance of 100 m and the 2.4 GHz unlicensed Industrial, Scientific, and Medical (ISM) band. A piconet is the most straightforward pattern of a Bluetooth network, and it is composed of the *master* of the connection (commonly, a gateway node), and a maximum of seven served active *slaves* (clients) [205].

The second primary wireless short-range technology is defined by the IEEE 802.11 standard, also known under the market name of Wi-Fi, which aims to provide connectivity to mobile devices within the Wireless Local Area Network (WLAN). A direct connection between devices is allowed by the ad-hoc mode foreseen by the standard, nonetheless, the lack of efficient power saving and enhanced Quality of Service (QoS) has pushed the Wi-Fi Alliance to make a move towards the Wi-Fi Direct option, which handles the P2P communications more efficiently [206].

Moreover, the current development of AR, VR, and XR technologies dictates the need for higher throughput and lower delays. Developers are opting for technologies that operate in high and ultra-high frequencies, e.g., Institute of Electrical and Electronics Engineers (IEEE) 802.11ad, IEEE 802.11ay, and IEEE 802.11ac that can provide Gigabit data rates in millimeter-wave band (mmWave) [207]. Moreover, the use of these high frequencies has its propagation limitations, which is ultimately an advantage for dense packing scenarios, where human bodies act as a natural barrier and allow better utilization of spatial reuse [208,209].

The Terahertz (THz) frequency band ranging from 100 GHz to 10 THz offers substantial bandwidth, theoretically enabling capacity in the order of terabits per second at negligible latency. The THz frequency band has been experimentally utilized for communication purposes at short and medium ranges [210]. Currently, the THz frequency band is a subject of exploration for point-to-point communication among regulators, operators, and manufacturers. Visible Light Communications (VLC) is among the connectivity solutions that operate in the THz frequency range, more precisely from 400 and 800 THz (780–375 nm). This technology can simultaneously achieve illumination and communication between two or more devices in proximity, thus improving energy efficiency using existing lighting infrastructure [211].

The wearable communication technologies with the shortest range correspond to Radio Frequency Identification (RFID)/NFC systems. RFID nodes can be worn by workers to provide them with hands-free operations and allow flexible and mobile asset tracking by being attached to gloves, hats, or helmets [212], and operating on the same 13.56 MHz frequency [213].

More advanced opportunities are brought to wearables by long-range technologies. In contrast to the short-range communication (with short-range technologies enabling a longer battery life, cheaper and less complex devices [214]), long-range ones eliminate the application selection limit, and wearable devices can communicate directly with an access point, a base station, or an edge node. As a result, some companies provide solutions for wearable devices with the opportunity for either physical or embedded subscriber identification module (SIM) cards to integrate long-range technologies. These solutions include models from Apple, Samsung, LG, and Xiaomi.

3.4.2. Long-range communication technologies

Motivated by the increased popularity of these solutions, 3GPP introduced its Massive Machine Type Communications (mMTC) technologies for low-power operation and reduced-complexity devices, namely Narrowband Internet of Things (NB-IoT) and Long Term Evolution (LTE)-M [179]. The introduction of these technologies paved the way for the usage of cellular modems in standalone wearables. First introduced in The 3rd Generation Partnership Project (3GPP) Release 13 specifications, both technologies are optimized to communicate small amounts of infrequent data with minimal power consumption and maximal coverage. Taking into consideration the traffic requirements of wearable applications that might be higher in comparison with smart city or other more common Low-Power Wide Area (LPWA) use cases, several enhancements to the NB-IoT and LTE-M standards are suggested in 3GPP Release 14 specifications to offer higher data rates while still consuming less power.

Nonetheless, presently deployed in cities, LPWA technologies are already utilized for cases of long-range communications and low energy consumption requirements [215]. The first target of these technologies was low-end IoT devices such as sensors. However, LPWA connectivity solutions have started attracting other application scenarios used in wearable systems. An example of non-lincensed LPWA technology is Long Range LPWAN protocol (LoRa). It is a long-range wireless technology that operates in the license-free ISM radio band at 868 MHz and offers transmissions up to 25 km operational distances. This technology has been deployed mainly in e-Health applications, such as temperature sensor-based wearable devices, to evaluate and predict heart failure events in high-risk patients [216]. Another alternative LPWA technology used by proprietary wearable devices is Sigfox, which, similarly to LoRa, operates at the sub-GHz ISM band and provides extended coverage. While LoRaWAN is based on a spread spectrum technology, Sigfox is a narrowband technology owned by the Sigfox company in charge of deploying their networks [217].

Table 3 provides additional technical details on the short-range and long-range communication technologies that are deployed in wireless networks for the support of wearable applications. It lists most modern ISM-band technologies ranging from conventional Wi-Fi to Wireless Gigabit Alliance (WiFi at 60 GHz) (WiGig) as well as paid-spectrum ones. In summary of this section, despite the conventional operation of wearable devices via relays, the next-generation wireless networks aim to provide standalone wearables with the opportunity of establishing direct communications with the cloud.

3.4.3. Device-to-Device (D2D) -based communication for wearables

Multiple works propose to support wearables through D2D communication to increase the wireless networks' capacity and coverage by enabling immediate communications between the users.

3.4.3.1. Task caching and offloading. The research community has extensively discussed the rapid growth in the amount of data and the number of computations on wearable devices. For example, the authors of [218,219] introduced a data-driven resource management framework to perform service-aware resource allocation and improve resource ratio utilization with D2D communications. More specifically, real-time communications between virtual reality and other wearable devices are based on Edge caching. In this scenario, using D2D technology improves the cache hit ratio by considering mobile caching and small cell caching – Base Station (SBS). Besides, D2D communications increase wearable devices' bandwidth in ultra-dense 5G and B5G cellular networks.

Moreover, the researchers have sufficiently covered task offloading strategies to minimize processing time and, therefore, save power for wearable devices with low battery levels. The authors of [220] propose using the D2D link to create mMTC and, thereby, overcome the limited resources of mobile devices. A similar approach is used in [221], where nearby wearable devices form a local mobile cloud and thus provide low latency. In [222], Dust (prototype code uploading D2D) uses Google Glass as a prototyping device and offloads tasks using D2D and the cloud. The authors of [223] provide computational offloading recommendations for AR applications running on wearable devices. In [224], the authors propose a data offload platform for other nearby applications and emphasize that Wi-Fi Direct D2D binds to maintain high data rates for locally linked groups compared to

Table 3
Wireless technologies comparison for wearable communication.

	Communication technology	Topology	Frequency bands	Range	Data rate	Power profile
Short-range	RFID	P2P	125–134 kHz, 13.56 MHz, 860–960 MHz	Up to 100 m	Varies with frequency	Very Low
	NFC	P2P	13.56 MHz	<0.2 m	Up to 424 kbps	Very Low
	BLE (IEEE 802.15.1)	P2P, mesh, star	2.4–2.48 GHz	Up to 100 m	Up to 24 Mbps	Low
	Zigbee (IEEE 802.15.4)	P2P, mesh, star	868–868.6 MHz, 902–928 MHz, 2.4–2.49 GHz	Up to 100 m	Varies with frequency	Very Low
	Wi-Fi (IEEE 802.11a/b/g/n)	D2D, mesh, star	2.4–2.48 GHz, 4.9–5.8 GHz	20-250 m	2-600 Mbps	Medium
	Wi-Fi 5 (IEEE 802.11ac)	D2D, mesh, star	4.9–5.8 GHz	Up to 70 m	Up to 3.5 Gbps	High
	Wi-Fi 6 (IEEE 802.11ax)	D2D, mesh, star	1–6 GHz	Up to 120 m	Up to 9.6 Gbps	High
	WiGig (IEEE 802.11ad/ay)	D2D, mesh, star	57–70 GHz	10–100 m	Up to 20 Gbps	Very High
	VLC (IEEE 802.15.7)	D2D, mesh, star	400–800 THz	Up to 100 m	Varies with frequency	Very High
Long-range	NB-IoT	Star-of-star	LTE frequency bands	Up to 15 km	Up to 250 kbps	Low
	LTE-M	D2D, Star-of-star	LTE frequency bands	Up to 10 km	Up to 1 Mbps	Low
	LoRa	Star	867–869 MHz	Up to 50 km	50 kbps	Very Low
	Sigfox	Star	868–878.6 MHz	Up to 50 km	100 bps	Very Low

Bluetooth and BLE. The context-sensitive upload structure (to cloud or smartphone) was developed in [225] to achieve a trade-off between the usability of wearable devices and the energy savings on the smartphone. As a result, the power consumption of unimportant tasks and the waiting time for urgent tasks are significantly reduced.

3.4.3.2. Software-defined D2D communication. To combat a problem of computational constraints and other critical issues faced by wearable communications (see Section 4.7), the authors in [214] propose multiple-layer communication architecture, which incorporates D2D cloud/edge technologies, Software-Defined Networks (SDN), Heterogeneous Cloud Radio Access Network (HC-RAN), Multiple Input Multiple Output (MIMO), and mmWave technology, among others. In [226], SDN architecture for supporting D2D communication between nodes of Wireless Sensor Network (WSN) is proposed to maintain connectivity even in the case of the cellular infrastructure failure or when it becomes partially unavailable. The authors particularly exploit D2D technology to build a mobile cloud and perform computational tasks on nearby devices. In the event of a disaster, the SDN controller selects a multi-hop routing path. Here, the Cluster Head (CH) on each mobile cloud associates with other CHs using inband D2D to convey the information of out of coverage devices to the other part of the network. Further, SDN based multi-standard cognitive radio is studied in [227] for heterogeneous wearable wireless networks. It can control, configure, select, and decide on switching between multiple technologies based on the specific requirements in D2D communications.

3.4.3.3. Millimeter wave-based D2D communications. Using the mmWave link is a tempting approach to achieve high data rates in wearable networks [228,229]. Moreover, the industry recognizes the importance of mmWave technology for high-quality wearable devices [230]. For example, the IEEE 802.11 working group is looking at high-performance, mmWave-based wearables in public places as a possible use case. As pointed out in [231], mmWave is an ideal candidate for D2D in very dense scenarios because it requires directional transmission to overcome high path losses, which in turn reduces interference between adjacent lines [232]. Meanwhile, D2D is also beneficial for mmWave picocells due to its high attenuation, especially for users at the cell's edge. Open areas of research in mmWave D2D communications, such as gaps in ML, channel modeling, D2D clustering techniques, green connectivity, and user mobility in mmWave D2D networks, are discussed in [233]. Another interesting topic is covered in [234], which discusses relay selection in mmWave D2D with dynamic obstacles.

3.4.3.4. Social-aware communication. Beyond the conventional connectivity and interaction between heterogeneous IoT and IoWT devices, the concept of Social Internet of Things (SIoT) supports a plethora of socially-driven collaborations among objects [235,236]. The synergy of social networking and IoWT paradigms offers some benefits and allows devices to socialize, collaborate, and establish group-communications according to the relationships. For instance, *Social object Relationship* includes conventional human social relationships (e.g., owners of devices are friends on Facebook, Linkedin, etc.), *Ownership object Relationship* brings together devices held by an owner, *Co-Work Object Relationship* integrates objects that work together to provide service for a common IoT application, *Parental Object Relationship* clusters objects belonging to the same production batch, whereas *Co-Location Object Relationship* combines devices in the same place. The concept of using elements of social networks in IoT has attracted an unprecedented amount of attention from the research community [237,238]. Not surprisingly, most of the research contributions in this field focus on devices and their owners, their particular aims and needs, and trustworthiness.

An overview of the integration of social-awareness and D2D communication is presented in [239]. More precisely, the authors offer state-of-the-art, socially-driven D2D communications by analyzing relay discovery and peer selection, communication mode selection, spectrum resource allocation, and management when social concepts are applied to them. In [240], the authors focus on social-aware D2D communications in 5G cellular networks using matching theory for caching problems. The authors state that the combination of D2D and content caching can considerably improve system performance. The work [241] presents a trust-based solution, where reliability and reputation of devices based on SIoT concept are used for effective D2D enhanced cooperative content uploading in NB-IoT. In [242], D2D communication is applied to acquire the context-aware information and integrate it with networking information elaborated at BS for information diffusion time estimation in the The Fifth Generation Cellular Network Technology (5G) network. In [243], the authors combine the Diffie-Hellman Key Exchange (DHKE) algorithm with the SIoT concept to efficiently allocate network resources to reliable nodes. In [244], a D2D-based group technique to operate in sensor network environments, which contains a vast amount of devices, is proposed. This approach allows reducing data congestion and ensuring outstanding power efficiency.

3.5. Localization

In recent years, the importance of wearable devices in our daily lives to provide location and tracking of users within an environment and their interaction with the plethora of Location-Based Service (LBS) has increased considerably. However, the wearables that perform these features present performance limitations in some scenarios and applications. Therefore, researchers are developing new positioning systems considering the latest wearable devices' strengths and limitations to counteract these limitations and increase the positioning performance. These new solutions include the implementation of new technologies, techniques, and methods.

Given the fast growth of wearable devices that use positioning and localization services, it is common to find them equipped with GNSS chips. Currently, GNSS-based navigation systems have about 158 satellites in orbit for positioning purposes.

Hence, some wearable devices can estimate the user's position by using GPS or other constellations. Some companies are implementing new technologies to provide highly reliable positioning services in wearable devices. For instance, in order to reduce the power consumption, Sony Corporation will incorporate a GNSS receiver in low profile devices when dual-frequency is used to compute the user or device position [245].

We can distinguish two main classes of positioning systems based on the main wearable architectures: infrastructure-based and infrastructure-less [246]. On the one hand, infrastructure-based systems are those systems that depend on a specific infrastructure to estimate the position. The infrastructure can be deployed exclusively for the system or be part of another system designed for a different purpose [247,248]. On the other hand, infrastructure-less systems work without requiring any surrounding infrastructure [249,250].

With respect to the application environment, wearable positioning systems are classified as indoor and outdoor positioning systems. In indoor environments, applications demand high accuracy position compared to those used outdoors [251]. Additionally, each environment presents particular challenges for positioning systems, for example, the occlusion of view of the skies due to ceiling and signal multipath due to the complex geometry of indoor environments. Therefore, depending on the type of environment, the positioning technologies and techniques implemented are diverse to face the environmental conditions [252].

In outdoor wearable positioning, the Global Positioning System (GPS) and the cellular networks are the most used technologies [252, 253]. Regarding cellular networks, in each of their generations, the positioning accuracy is improved. Since the second to the fifth generation, the actions carried out to improve the positioning accuracy are: use the cell-ID localization technique, timing via synchronization signal, specific reference signal designed for localization, and using all the layers of protocol stack [254]. The technologies most used for indoor positioning are: BLE, Wi-Fi, RFID, NFC, Ultra-Wide Band (UWB), Light, Computer Vision, Magnetic Field, Sound, Dead Reckoning, and Tactile Odometer [255].

In addition to traditional positioning systems, more complex systems have been proposed to enhance positioning accuracy and performance. For example, Collaborative Positioning Systems utilize neighboring wearables/users in the positioning system method, and systems based on sensor fusion combine diverse sensor information to reduce the estimation error of position [256].

Localization can significantly enhance the capabilities of wearables. For instance, it can help users navigate and provide clues to devices about interacting with users based on their location. Besides, location services play a crucial role in emerging fields such as assisted living, smart homes, and smart cities. Thus, the recent Location-Based Service (LBS) must be compliant with the current legislation in terms of privacy and security [257].

To summarize, choosing a suitable localization technology depends on the application requirements. Table 4 compares some of the most popular wireless technologies that can be used in the localization of wearables. Some technologies are already present in wearables (GPS, Wi-Fi, or BLE) but have accuracy in the range of dm to m. UWB and RFID-based localization technologies are relatively accurate but are infrastructure-based.

3.6. Interoperability

The integration of multiple subsystems is the basis for modern IoT and IoWT systems. However, it generates new interoperability problems and requires additional attention from the industry and research communities to create seamless programmability of the various things to connect, collaborate, and effectively exchange the data among them [277]. Moreover, interoperability faces diverse challenges under different scenarios in various fields and domains.

Different factors can trigger interoperability issue [278]. For instance, integration between different manufacturers, limited communication between different transport protocols, and no established rules or standards at the application level can prevent seamless integration. In this context, it is essential to manage the intrinsic heterogeneity of IoT systems and provide effective solutions for seamless interoperability among smart devices, sensors, etc. Accordingly, interoperability is investigated from various perspectives, including device, technology, network, syntactic, semantic, and platform [279].

3.6.1. Device interoperability

IoWT is composed of a wide variety of smart objects or things ranging from high-end to low-end devices. The former have sufficient resources and computational capabilities, whereas the latter type of devices is generally resource-constrained. However, the devices, which are different in terms of computational capabilities and use different communication technologies, may need to exchange information. This challenges interoperability among various types of heterogeneous devices of the IoT ecosystem. Device interoperability is related to the data exchange between heterogeneous devices and communication protocols and the possibility of integrating new devices into any IoWT platform [279].

3.6.2. Network interoperability

The integration of the IoT heterogeneous systems requires interoperability at various protocol levels to work together [278] seamlessly. This interoperability type deals with mechanisms that enable seamless, ubiquitous connectivity. To truly ensure network interoperability, each system must be able to provide the data exchange with other systems over different networks by focusing on such network layers functions as addressing, routing, mobility, security, and resource optimization [280].

3.6.3. Syntactic interoperability

As mentioned above, interoperability reflects the ability to exchange information transmitted between systems in the form of messages. In this context, a message can be studied on the syntactic level, where its internal properties are considered. Syntactic interoperability refers to the interaction of format and data structure used in any exchange between the IoT heterogeneous objects and can be reached through defined data and interface formats and encodings [277].

Table 4
Comparison of localization technologies for wearables.

Technology	Refs.	Accuracy	Maximum range	Power consumption	Localization approach used	Advantages	Disadvantages
GNSS (GPS)	[258,259]	10 cm	Global, outdoors	0.5–2.5 W	Time-based	Global, widely-available.	Only outdoors, low accuracy, high power consumption.
Wi-Fi	[246,260–262]	dm- or m-level	250 m outdoors, 50 m indoors	<1 W	Fingerprinting, AOA, TOA	Widely-available, low-cost, often does not need dedicated infrastructure.	Good-accuracy localization methods based on fingerprinting require extensive training, relatively low accuracy.
UWB	[263–265]	Order of cm	300 m	100–500 mW	TOA, AOA	High accuracy and precision, moderate costs.	Not widely-available (yet), needs dedicated infrastructure.
BLE	[266,267]	Order of m	100 m	<50 mW	Fingerprinting, TOA	Widely-available, ultra-low-power, protocol stack suitable for the IoT.	Low accuracy.
Non-visible light	[268]	Sub-mm	10 m	N/A	TOA	Very high accuracy.	Requires LOS, expensive.
Visible light	[269,270]	cm- or dm-level	1.4 km	N/A	TOA	Can use ambient light sensors commonly available in smartphones.	Requires Line-of-Sight (LOS), high-accuracy solution requires dedicated hardware.
LoRa	[271,272]	m-level	20 km	<100 mW	AOA, RSS	Ultra-low-power, low-cost, long-range, designed for the IoT and sensor networks.	Low accuracy.
RFID (passive)	[273,274]	cm-level	15 m	–	AOA, POA	Ultra-low-power, low-cost, high-accuracy.	Expensive infrastructure, small coverage area.
RFID (active)	[125,275,276]	m-level	150 m	<100 mW	RSS	Low-cost, medium range.	Moderate accuracy, need to be powered.

3.6.4. Semantic interoperability

The need for semantic interoperability emerges when heterogeneous devices use different syntax to encode and decode their information [281]. For instance, reliable communication between the source and gateway devices can be interrupted if a sink device fails to decode a source data format into an understandable form. In addition to the fact that the data generated by wearables may have defined data formats, the data models and schemes exploited by different sources are usually dissimilar and not always compatible [279]. Further, the data may consist of different information and be represented in other measurement units. This semantic incompatibility between the data and information models leads to IoWT systems' failure to dynamically and automatically inter-operate (as they have different descriptions or understandings of resources and operational procedures [282]). To this aim, semantic interoperability enables different agents, services, and applications to exchange information, data, and knowledge in a meaningful way, on and off the Web.

3.6.5. Platform interoperability

Platform interoperability issues arise in IoWT due to different operating systems, programming languages, data structures, architectures, and mechanisms for things and data. The lack of platform interoperability can lead to the inability to connect IoWT devices to heterogeneous platforms, developing applications that use multiple platforms, and delaying the implementation of IoWT technologies on a large scale. In contrast, cross-platform interoperability will ensure broad collaboration between platforms to offer the best solutions in different areas [283]. To this end, one may need to acquire comprehensive knowledge about Application Programming Interface (API)s and information models of platforms to adjust applications from different platforms [279].

Although IoT interoperability issues are addressed by several academic and industry studies, there is still no proper foundation that can cover some related research issues discussed later in Section 4. The lack of standards and the absence of cutting-edge technologies slow IoT development. Therefore, interoperability is a challenge that needs to be extensively studied to provide consolidated, reliable, secured, scalable, and adaptable solutions for IoT networks. Seamless IoT device interoperability is believed to push and open the massive opportunity in the IoT market, accelerate industry innovation, and help developers and companies produce solutions quickly.

3.7. Mass consumer directions

In this section, we first overview the main wearable development activities happening in the industry and proceed with the literature review on recent academic works in the area.

Generally, the wearable devices' market is flooded with new solutions developed at both the academic and industrial levels. This subsection provides a vision of a variety of prototypes and research directions present in the industry. The next subsection would give an overview of the leading academic projects and activities. Note that this subsection particularly focuses on projects that are not yet present on the market. A detailed overview of ready-for-purchase devices (together with prototypes) is given in Appendix.

Moreover, today's mass-market of wearables is driven by corporations aiming to push the adoption of high-end wearables to customers. For example, Samsung is the most prominent owner of wearable patents, counting 3421 [284] active ones. At the same time, Samsung was the global leader in the number of granted patents in the years 2010–2018, counting 796 [285] granted patents.

While focusing on other industrial giants together with Samsung (Microsoft, LG Electronics, Sony, Alphabet, Epson, Philips, BOSE, Apple, and OPPO Electronics), their intellectual property concerns more than 50% wearables. Therefore, more applications of market-available wearables include monitoring of disabilities, education, enterprise, finance, gaming, and entertainment. In general, the Asia–Pacific market is the most active in the world in this area.

3.7.1. Entertainment and AR/VR/XR

Concerning entertainment, another fast pacing wearable market niche is related to VR devices. The adoption of said technology was previously limited by hardware and communication issues, i.e., low computational power and high bandwidth that were not reachable with conventional wireless systems. Today, several VR headsets could be purchased with reliable wireless connectivity while keeping the user experience on a high level [208].

Companies are also integrating positioning and heading into their state-of-the-art devices. A clear example is Sony, which is developing a HMD. The contents on the HMD are adjusted depending on the user's pose and position to provide a full augmented reality experience for gaming on other applications [286]. Thus, the position and heading are essential, but the head tilt is needed to re-allocate the elements on the screen. Although the positioning techniques are well-known and most of their problems are already solved, they face the restriction of energy consumption imposed by the gadget size. Therefore, their efforts are dedicated to the efficient combination of all the available sensors, as demonstrated in [287].

Another area of interest includes Industrial Internet of Things (IIoT) field. In particular, RealWear company focused on products specifically designed for connected enterprise employees to increase job satisfaction, productivity, and, most importantly, safety [288]. The company has been developing an industrial hands-free portable computer for many years, aiming to improve the employee's situational awareness, providing vital information on demand in the harshest conditions. Today's technology combines a small Android computer and a camera, speaker, and microphone in a tiny screen project information in front of the user's eyes. This rugged hard hat is an intelligent headset that works similarly to the original Google Glass but uses the underlying technology in a completely different way.

Another project called Kopin Golden-i Infinity is also designed to improve workers' life with AR technology [289]. The device is used to understand better the repair guidelines for field maintenance, access to production plans, view utility, and energy information, collaborate with remote experts, and more. Besides, the device boasts a nine-axis stabilization head, triaxial accelerometer, gyroscope, and magnetometer. This sophisticated tracking system evaluates the effect of the Earth's magnetic field on the user's geographic position and head movement, providing unprecedented tracking accuracy for applications requiring incredible accuracy. Kopin also develops medical AR glasses for surgery purposes [290].

Nonetheless, Nsoft and Trimble made a hard hat with Microsoft HoloLens XR headset built-in specifically for industrial workers [291]. The XR10 is a customizable helmet with an integrated rotatable HoloLens 2 lens that allows construction work to be visualized on site. This first partnership is a clear sign of where Microsoft hopes to go with its second-generation headset, taking the technology outside of the office to real-world sites.

Keeping AR and VR headsets as a standalone solution is a trend for heavy machinery, crate, drivers, and maintenance employees that do not require constant mobility. However, complex computation on head-mounted devices is still challenging due to battery and computation limitations and overheating issues. Company Zebra produces portable computers aiming to overcome those issues [292] and potentially offload the computations to powerful yet portable wearable cloud nodes. Complete Zebra solutions are based on Android enterprise devices delivering unrivaled scan performance and manageability. Zebra's fully wearable solutions combine mobile with wearable technology and ease of pairing features providing the operational flexibility needed to exchange complexity for productivity.

Started with Google Glass, many companies aim to develop personal AR-based assistants. One of those is the well-known Vuzix [293], which aims to develop next-generation AR smartglasses using MicroLED Technology with the primary goal of miniaturization of the integrated screen.

Interestingly, Tesla files a patent for Google Glass-like AR system for faster, accurate vehicle production [294]. According to the patent application, the technology uses computer vision to recognize objects based on the object's colors displayed on the camera view and the device's location. The recognized object is then compared with the 3D model library's corresponding model and overlaid on top of the digital data.

In contrast, Bose AR with audio provided an entirely new dimension of audio immersion by merging Bose AR technology with sunglasses [295]. The device detects where the user's location and which direction the owner is facing via a nine-axis head motion sensor and the GPS on tethered Android or iOS devices. The audio pumped through the on-board headphones changes accordingly. A new wave of head-mounted wearables is related to VR. During Mobile WOrld Congress (MWC), Nreal Light smartglasses provide mixed reality for the masses [296]

Indeed, enabling an enhanced immersion in other realities could not be possible without easy-to-use assistance devices. One of those is a haptic VR suit for industrial training. Brian Heater developed by Valkyrie Industries [297]. Similarly to the Iron Man suite aims to provide the "haptics is the sense of touch, particularly relating to the perception and manipulation of objects using the senses of touch and proprioception". Interestingly, the suite is designed not for gaming but for professional applications, the list of which is kept untold.

3.7.2. Medical and close-to-medical devices

A massive sector is related to close-to-medial wearable devices, i.e., ones that are not certified as medical ones but still aiming to detect some health-related issues. For example, a French piece of technology, Crhonolife smart vest, presented at the Consumer Electronics Show (CES) 2019 event, aims to predict the heart-attack before it happens [298]. It is specifically designed to prevent medical emergencies in patients with congestive heart failure (CHF). Some devices are designed to monitor the owner's posture, including Upright and Lumo Lift [299]. Many companies, including POLAR, Garmin, Fitbit, and others [300], allow for heart rate monitoring but often do not focus on Food and Drug Administration (FDA) approval.

On the other hand, some medical wearable devices have also succeeded in receiving FDA approval, including the well-known Apple Watch [301] for the detection of falls and irregular heart rhythm, thus, achieving Steve Jobs' goal. Nonetheless, SYNCHRONY and SYNCHRONY 2 cochlear implants have also received the approval for people with single-sided deafness (SSD) and those with Asymmetric Hearing Loss (AHL) [302]. Next, Neofect's powered glove for people with paralysis is shipping this summer [148]. It provides the users with mobility in a paralyzed hand (potentially present due to stroke, Multiple Sclerosis (MS), and Amyotrophic Lateral Sclerosis (ALS). It allows performing simple everyday tasks such as brushing their teeth, opening doors, or drinking from a cup.

Another active niche of wearable industrial research leads to an artificial nervous system [303]. Researchers from NUS Materials Science and Engineering developed the touch equivalent to human skin with the Asynchronous Coded Electronic Skin (ACES). It can assist future robotics in terms of providing sensual feedback for tactile feedback in prosthetics.

A lot of research activity is currently executed related to Parkinson's disease. Based in Austria, EVER Pharma recently received CE Mark approval and is releasing its D-mine Pump in Europe [304].

Patents have also shown the trends for medical wearables. In [305], the authors introduce a wearable device integrated into a partial or full body soldier's garment, able to deliver wound sealant to an injury and activate selective small balloon inflation to add pressure to a wound. An alternative use-case considers its usage to stabilize the injured while being transported.

Honda Motors patented a method to support the vehicle control [306]. The wearable devices can capture diverse physiological data to determine one or more vehicle occupants' health state. These data, such as the blood rate pattern, can also be used to identify a vehicle occupant. Their method includes the total or partial control of the vehicle based on its occupants' health state.

3.7.3. Fashion and comfort

A massive niche is allocated to the mass consumer by means of improving the comfort of everyday activity and fashionable look. The number of devices ranges a lot, from luxury smart rings to invisible personal assistants.

An exciting segment of wearables is novel wearable air conditioning systems. To name a few, Sony Reon Rocket is a body-cooling wearable that promises to chill the owner in the heat [307]. Sony is not the only company attempting to capitalize on the rising heat. Embr Labs is a startup founded by three MIT graduate students who were frustrated that it was always freezing in their lab in the summer, even when there are only a few people in the building [308].

3.7.4. Consumer sports

Besides the conventional market segment of activity trackers and smartwatches, few more vendors focus on the development for a specific group of users — athletes aiming to improve their results utilizing better monitoring and improved training [309]. Catapult [310] and STATSports [311] are trendy suppliers of wearables to the top sports teams in soccer, football, hockey, rugby, and baseball. These producers offer small devices worn in the special vest pockets on the back and can perform indoor and outdoor localization and track the heart rate. Specially developed software performs analysis based on collected data and allows to manage workloads, monitor athlete progress, and avoid situations that could lead to injury.

The authors in [312] introduced a wearable device used to record fishing data. The wearable can receive motion data from one or more motion sensors. Collected motion data is analyzed to determine if it corresponds to a casting motion while fishing. In such a case, the cast occurrence is recorded and timestamped.

Xsens [313] developed a real-time motion capture system named MVN Analyze, which allows accurate tracking and analysis of the athletes' movements even during high-intensity activity. The system is available in two versions: 17 wireless sensor straps (MVN Awinda) or a Lycra suit (MWN Link) — both comfortable for the user and not restricting his movement.

Another promising niche is related to the growing vehicular market [314,315]. In particular, wearable devices may be used to assist in continuous passenger biometrics monitoring during the autonomous vehicle operation, thus, improving the overall safety of the system [316]. These include authentication while accessing the vehicle, passenger presence, driver's biometric status, sleep monitoring, etc.

3.7.5. Security

A sector with great research potential for wearables is related to the information security domain. Already today, wearable devices may enable safe transactions/payments on a mobile device based on a wearable security token. It not only separates the security management from the device performing the transaction but also reduces the risk of impersonation or relay attacks [317]. Similarly, other wearable devices have been patented to, for instance, safely store encrypted information, which is only sent to a pre-specified mobile terminal after verification [318]. Some wearables combine biometrics and advanced encryption to allow specific secured transactions with a counterpart communication device/system [319].

However, wearables are not only used for secure monetary or information storage/transactions. The authentication possibilities through biometrically secured access may also be used to, e.g., automatically manage other smart devices [320] or send alerts in response to critical situations according to the wearer's vital signs [321].

3.7.6. Other industrial activities

Some smaller companies are involved in developing novel niche solutions and creating new applications. The examples are wearables for well-being. Relaxation is a part of wellness that corresponds to the fashion and comfort segment of wearables. The Silentmode's PowerMask is a relaxation mask that keeps records of heart rate variability, as stated in [132]. The Dreamlight Zen meditation & sleep mask is a product that uses lights and music to help users calming down and restoring their vitality.

The possibility of wearable devices to sense and act has also found applications in stimulating sensitive parts of the body and/or measure signals. In the adult entertainment market, various wearables were designed to induce sexual pleasure. Besides practical products, some design and technological efforts have been made to separate the drive means from the stimulation means, enabling a fully autonomous operation [322], or, even, to allow remote controlling [323]. Other bodies and muscle stimulation applications are also explored, for instance, to tackle incontinence [324].

3.7.7. Active (Inter-)national projects

While industrial giants aim to occupy more significant shares of the market and increase their revenues, the academic sector is mainly focused on promising technologies and evaluating existing devices' performance.

A number of the international EU H2020 research projects are focused on wearable solutions both from the Hardware and the Software domains. Some of the ongoing projects are as following: Wearable Electroactive Fabrics Integrated in Garments (WEAFING) [325], Smart and Flexible Energy Supply Platform for Wearable Electronics (Smart2Go) [326], Personalized Body Sensor Networks with Built-In Intelligence for Real-Time Risk Assessment and Coaching of Ageing workers, in all types of working and living environments (BIONIC) [327], Real-time Analytics for the Internet of Sports (RAIS) [328]. Moreover, more than 400 projects related to wearables have received support only from the EU since 2016.

From non-EU perspective, exceptional sense of touch for robots is described in research [303,329]. As the device is called, ACES has a somatosensory perception, which identifies a touch 1,000 times faster than humans' nervous system. A potential application for this technology will allow performing critical surgery with better responses and taking relevant actions in limited time slots.

Another project, described in [330], refers to the approach where scientists present ultrasoft electronics as a concept for Body Area Network (BAN). The researchers in [331] have developed a sample of heart cells with a soft sensor and changed the way of embedded medical devices.

The work described in [332] claims to create Magnetic Resonance Imaging (MRI) detectors that fit like a glove. The developed solution covers the situations where the hand moves in the magnetic resonance scanner without degrading the signal quality, thanks to the MRI detectors that seamlessly follow the contours of the hand using separate flexible high impedance elements.

The activity in [333] presents a novel approach to using the NFC technology to extract valuable knowledge from sweat analysis. This study proves to cover a gap as a non-invasive solution working on advancing the deployed sensors' form factor. Another study in [334] focuses on sweat analysis and claims wearables could analyze the data to get more insightful information regarding the user's physical and mental state for improving the quality of training.

Overall, it can be stated that financial agencies are interested in investing research funding in wearable technology research activities. Interestingly, those are not anymore limited to eHealth and medical domains, thus, allowing to cover activities in other fields.

3.8. Section summary

This section outlined the classification of wearable devices based on, e.g., location on the body, application type, functionality, etc. It highlighted the communication technologies, architectures, and related paradigms, including technical details, elaborated on various data processing-related aspects, and involved computing paradigms, outlined localization strategies for indoor and outdoor operation, and provided insight into the interoperability aspects, and, finally, delved into the mass consumer market status. Additional information on the devices is detailed in Appendix.

4. Open challenges and future perspective

This section outlines the majority of modern problems related to wearable data processing, privacy, security, and transmission aspects. Next, localization and communication-related challenges are drawn, followed by the adoption, hardware constraints, interoperability, and scalability aspects.

4.1. Data acquisition and processing

A large part of the data acquisition challenges is in the first component of the data processing chain, namely the wearable itself. The quality, quantity, resolution, and other parameters of the data are defined there. As crowdsourcing gathers data from multiple users, multiple devices, all in different scenarios and often using relatively cheap and energy-efficient sensors, the quality of the data itself can enormously vary across all individual data sources [335]. The quality and quantity can be related to spatial resolution, temporal resolution, or data resolution itself [160]. Spatial resolution determines the physical distance between two consecutive measurements from a single source and can be equidistant or strongly varying. Temporal resolution describes the time intervals between the two measurements from a single user and can be uniformly distributed or strongly randomized. The data resolution relates to the accuracy of the measurement sensors equipped in the user wearable, device-specific processing inside that wearable, and outside factors affecting the measurement itself.

The subsequent challenge lies in the large-scale data gathering process, i.e., finding the optimal method of gathering the users' measurements for further utilization [336] and its energy-efficient transmission. The question of privacy, security, trustworthiness, or user selection is nowadays still an open challenge [337].

Data processing challenges also describe the difficulties in data utilization after the acquisition phase. As mentioned above, the data have different spatial and temporal resolutions and varying data quality. Converting raw, gathered data into useful data is the main task of data pre-processing. The challenge lies in unifying the measured quantities' parameters and removing errors and statistical outliers from the data. Further data analytics require a clean input dataset and represent a consecutive challenge itself. The efficiency of the analytics determines the amount of useful information extrapolated from the set of individual measurements. Nowadays, wearable-related data processing solutions utilize machine learning techniques more often [338,339].

One of the main challenges of wearable data processing is the lack of a sufficient amount of data. To overcome this issue, a few categories of the time series data augmentation were proposed [195]. One of them is the augmentation in the time–frequency domain with wavelet transforms as one of the potential successors in augmentation of non-stationary time series and non-Gaussian noises [195]. Moreover, the combination of augmentation methods dedicated to imbalanced datasets from the used architectures weighting is also proposed in [195]. However, using data augmentation methodology brings potential problems, such as not reflecting the real data and possible overfitting.

Next, the lack of etiquette of the data states an extra problem because of the limited number of available datasets. Additionally, obtaining high-quality labels is time-consuming and often requires specialists for this purpose or engagement of the users [340,341]. One solution is to use a semi-supervised methodology when the number of the annotated labels is small. It could primarily be applied for the data gathered by sensors and wearable devices with long records, e.g., the Human Activity Recognition (HAR) task when not all the labels are correctly reported by the users or labeled by the specialists [341]. These same semi-supervised methods minimize the obstacles connected to training the data lacking in labels.

HAR was successfully used in temporal assembling of deep LSTM [342], LabelForest [343] or bi-view semi-supervised learning method [344] leading to the understanding that it may be a promising solution for classification tasks based on wearable data. Additionally, combining many modalities for detecting diseases allows decision support methodologies for achieving higher quality results in prediction. The limited number of works leaves a huge research gap, leaving ample opportunity for future directions. The multimodal approaches were used mainly hitherto for the human activity recognition [39], Parkinson detection [345], difficulty in cardiorespiration [156].

A new trend of wearable technology for data gathering becomes possible with the development of smart tattoos constructed from thin-film polymers, metals, ceramics, 2D materials, and their integration with rigid ICT [346]. Part of the smart tattoos will serve for the biomedical tasks, i.e., gathering physiological parameters in real-time [347, 348], e.g., the genetically programmed cells could be transferred into wearable devices.

Interestingly, smart tattoos were designed by Nokia as Vibrating Tattoos, which are placed on the skin. They contain ferromagnetic ink and vibrate when someone is texting or the mobile phone is calling. Princeton and Tufts University developed the next unique smart tattoo to measure bacteria levels in the mouth based on saliva with electronic wireless tattoo [346].

Additionally, recent micro- and nanotechnology developments support non-invasive biomedical measurements and wearable in-body and on-body sensing, processing, and communication. Examples of existing solutions are insertable cardiac monitors, continuous glucose monitors, Insertable Drug Deliverables Systems (IDDS). Shortly, the development of the analyte monitors is being expected (for example, for monitoring the oxygen concentration in interstitial fluid), insertable EEG monitors (dedicated mainly for epileptic patients), eye health monitors (for glaucoma patients). The most promising solutions are controlling the infant, therapeutic drug monitoring, and delivery [124]. Furthermore, the microneedle sensors' usage will allow clinicians to monitor the electrochemical parameters, for instance, measuring the level of levodopa for Parkinson's patients [349]. However, the main challenges of the insertables belong, among others, the foreign body response, which impedes the biosensors' functioning, likewise the transmission of the data or unexpected migration of the device [124]. One of the approaches for reliable wearable platforms is to address the optimal choices of sensors and user interfaces and conduct the validation of methods based on the target application (e.g., clinical, social well-being, etc.), data security and confidentiality, decision support, and user acceptance.

Significantly, the eHealth segment is a strongly regulated sector with high accuracy and reliability requirements. Mass-market wearables' accuracy cannot compete with often expensive hospital devices, and currently, available consumer wearables are usually not acceptable for medicine purposes. The reason is that wearable sensors often have insufficient accuracy compared to laboratory devices. Another issue is that devices from different production series can also suddenly measure different values due to different electrical components, which in the case of medicine can have serious consequences [350].

Crowdsensing data collection provides a significant advantage for wearables over large and accurate laboratory sensors. It becomes an effective and low-cost approach for automatic multi-purpose data gathering and processing [351]. Nowadays, it is commonly used, for instance, to automatically generate radio maps or collect health parameters for eHealth monitoring and activity recognition. Crowdsensing over wearables has many unresolved challenges, which include data redundancy and outliers' identification and elimination, reducing the data processing, transfer, and storage costs, leveraging the temporal and spatial correlations of information to reduce the amounts of stored and processed data, and dealing with heterogeneous devices and technologies [351]. Wearables can collect a variety of user-centric data, such as location-related knowledge, information on the user's well-being or health [352], and radio communication-specific data.

The development of the eHealth/mHealth field by applying wearable sensors is also of particular importance due to the rapid growth of the elderly population in Europe. For example, monitoring the elderly suffering from civilization or neurodegenerative diseases could allow to detect of Parkinson's or Alzheimer's disease early and predict the illnesses' development [353].

Approximate computing is another technique that allows to trade precision in exchange for increased energy and performance [354]. Many wearable applications, including ML, signal processing, image processing, Big Data analysis, and more, may not require very accurate results. Instead, results that are "good enough" can serve this purpose [355]. Thus, approximation has become an effective method for improving the performance and energy efficiency of devices with limited resources, such as [356] wearables. However, this comes with many issues, such as determining the minimum required accuracy, defining approximate problems, and monitoring the results of the application [357]. Hence, efficiently implemented approximation methods can achieve optimal performance gains in latency, execution speed/-time, and battery consumption.

4.2. Data transmission aspects

As we move towards a more connected ecosystem, data generation will continue to increase, primarily due to 5G and beyond technologies that ensure faster connectivity. However, not only technologies are developing, but also the problems that surround them.

Although a centralized cloud has traditionally been used for data management, processing, and storage, it has two major problems: (i) the latency to process data may be critical; (ii) all this data creates a significant load on the overall network performance. In contrast, Edge computing offers a solution to latency by moving critical data processing to the network's Edge [358]. Edge devices can collect and process data in real-time, allowing them to respond faster and more efficiently. However, there are issues related to the devices' capabilities, including developing software and hardware to handle the cloud's computing load.

Different computing paradigms demonstrate great opportunities and introduce new techniques to improve system performance. In practice, computing paradigms are sometimes discussed as mutually exclusive approaches to network infrastructure. Although they may function differently, utilizing one of them does not preclude using the others. In this context, some approaches have been proposed to solve this issue (e.g., a cognitive IoT Gateways [359], a platform that automatically determines the best environment to execute a task [360], and a framework for scheduling applications over a hybrid public–private cloud [361]). However, the automatic switching between computing paradigms is a challenge for future research, in any case.

It brings the researchers to the problem related to the migration of services or a Digital Twin (DT) of the wearable device, for instance, from one Edge server to another [362,363]. When a user moves across different geographical locations [364], e.g., from home to the workplace, the service/DT may follow the user's device. However, the determination of an optimal migration decision is challenging because of the trade-off between the migration and data transmission costs [365]. On the one side, migrating a service/DT may incur network overhead or even interrupt the connection. On the other side, not relocating a service/DT may increase the data transmission delay between the user and the edge server. In the literature, there are several approaches to reduce the transmission delay in traditional wireless communication networks concerning the migration procedure [366–368]. However, ensuring seamless migration among Edge servers is still an open problem that needs to be investigated.

Next, compressive sensing is gaining increasing popularity from the lower layers perspective, especially for IoT applications that involve sparse data signals. It is a signal acquisition and reconstruction technique that enables the receivers to reconstruct the actual signal using significantly fewer samples than required by the Nyquist criteria. Compressive sensing has proven to bring several benefits such as efficient bandwidth and energy consumption, which are the two most vital network resources in wearable networks [369,370].

4.3. Security and privacy aspects

In the previous subsection, we highlighted that wearable technology's main features are sensing and collecting data continuously. Therefore, with the advancement of the IoWT in next-generation cellular networks, security and privacy are vital characteristics for consideration in wireless communication scenarios [371]. Regarding the widespread of modern data collection techniques and sensor development, user concerns about reliability and trust in online platforms and location-based services are continually growing. The authors of [372] state that most modern devices include built-in sensors, which provide accurate location data and information about physical activity level and mental health. The study shows that the data is easily accessible and does not correlate with users' awareness. There is no unified solution to cover all threats in wearable technology security. Thus, further research and development are required.

4.3.1. Data-related aspects

In [392], the authors show concern about the actual owner of the data collected via smart connected devices. Due to the proximity to a human body, hereinafter, we claim wearable technology is one of the most exposed wireless solutions to privacy threats. Privacy issues are relevant to data integrity, and an attacker might physically affect the owner via malicious hardware or software. As long as embedded sensors in smart wearable devices crowdsource personal information about technology users, data processing should be privacy policy compliant. There are specific laws in countries worldwide that protect the data privacy of their citizens. Currently, the primary document in charge of data privacy and security protection in Europe is the General Data Protection Regulation (GDPR) law. This document implements newer focus areas, such as privacy rights, data security, data control, and governance. Accordingly, all data collected via wearables can be considered sensitive (e.g., genetic, biometric, and other health-related data). Consequently, our survey provides a taxonomy for multiple types of data that wearable devices are gathering via built-in sensors in Table 5. As this survey investigates, the most popular solution to exchange data on wearables is BLE, and many research experiments report on its vulnerability to security attacks.

Evidently, in most of the security and privacy preservation scenarios, it is necessary to perform complex cryptographic operations, which are limited in wearables due to their low computing power and limited resources.

4.3.2. Impact on energy consumption

The execution of the related complex operations implies, in most cases, extra consumption of energy and resources, which considerably reduces the duration of the battery. Despite the mitigation strategies already discussed, these drawbacks mean that it would be an excellent starting point to reduce the potential risk of future attacks. Their real implementation on wearable devices becomes quite challenging. Today, developers and researchers explore wearable technology's security aspects, especially in the medical and industrial segments. The authors of [393] investigated the executability of various primitives used in symmetric and asymmetric cryptography, block ciphers, elliptic curve cryptography, and conventional hash functions. The set of measurements showed that the use of widely used methods leads to a significant computational load on wearable devices compared to, for example, smartphones. As one of the solutions, this work highlights the need to develop specific lightweight primitives, taking into account the trade-off between energy consumption and safety as one factor in creating efficient devices with limited resources.

Table 5
Taxonomy of sensors and data collected via wearable devices.

Sensor	Biometrics	Location	Audio/Video	Altitude	Inclination	Health data	Other	References
Gyroscope		✓			✓			[373]
Accelerometer		✓					✓	[373,374]
Altimeter		✓		✓				[375]
Proximity sensor		✓						[376,377]
Temperature sensor							✓	[378]
Magnetometer		✓					✓	[379]
IMU		✓			✓			[380]
Camera		✓	✓				✓	[167,381]
Optical sensors		✓				✓		[382,383]
Microphone			✓					[381]
Beacons		✓						[384]
Chemical sensors						✓		[385]
Antenna module		✓						[386,387]
Ambient light sensor		✓					✓	[388]
NFC sensor		✓					✓	[389]
Touch sensor	✓							[390,391]

4.3.3. Privacy aspects

Nonetheless, from Radio Access Network (RAN) perspective, several entities can be considered to have access to the most sensitive data collected by wearable devices. The actual device might be an adversary to data integrity and security if not enough safety measures are considered or no encryption has been used.

Since most of the wearable communications utilize D2D solutions, i.e., when multiple devices are communicating in proximity (e.g., execute any collaborative tasks), securing those links became an essential field of research [394]. D2D nodes in the proximity can share sensitive information about the user identity and other personal data. As a consequence, this personal information can be exploited for illegal purposes by eavesdroppers [206]. Network security protocols in D2D networks were developed to allow users to avoid any information leakages. The major issue primary in secure D2D networks is the dynamic readjustment required due to user mobility. Therefore, the need for an adaptive mechanism for D2D network security emerges when the users join or leave the coalition [395].

To conclude, although there has been a plethora of work related to wearable architectures for efficient dynamic D2D communications, the following topics are mostly missing in the literature: multi-connectivity heterogeneous Radio Access Technology (RAT)s and mobility in the IoWT, optimized link selection for highly dynamic multi-tenant networks, need for efficient privacy-preserving techniques, security issues, the enhancements offered by a set of innovative 5G technologies in practical IoWT contexts, among others. There are still no appropriate communication architectures to converge wearable devices and networks with external Internet via the edge-computing infrastructures allowing seamless and well-orchestrated integration and interoperability. Therefore, multiple design choices and criteria need to be thoughtfully studied in this field. For instance, the Inside-the-body (ITB) component of the network could be connected to the user's equipment (e.g., a smartphone or high-end wearable device). These require real-time access to the proximate edge cloud ecosystem, which offloads the battery-constrained devices and processes their demanding computing tasks remotely. This construction became even more challenging when a user is on the move, and numerous technical challenges need to be resolved in high dynamic scenarios.

4.4. Localization aspects

Modern wearable technology heavily relies on the precision of positioning techniques embedded in the devices. This subsection lists the main challenges related to the localization of resource-constrained wearable devices.

To start with, the geometry of indoor scenarios plays an essential role in the robustness, precision, and accuracy of the positioning systems used on wearable devices. Mainly because the dominant positioning technology used by wearable devices relies on wireless technologies, e.g., BLE, Wi-Fi, UWB, with various signal propagation problems being present due to the complexity and continually changing of indoor environment [396]. Factors alter the signal propagation as propagation losses (e.g., reflection, diffraction, scattering), Non-Line-of-Sight (NLOS), multipath propagation [396,397].

NLOS propagation radio signal is the primary source of the inaccurate position, so mitigating its effects is one of the main challenges in positioning [398–400]. A vast amount of methods for mitigating the effects of NLOS on position accuracy has been proposed. For example, the authors of [398] classify them into two categories, methods that mitigate the NLOS into the positioning algorithm without previously identifying NLOS and methods that implement a NLOS identification phase first and then, in a second phase, mitigate the NLOS error from the position estimation. In [401], the authors consider a cooperative positioning approach to address the NLOS estimation error issue. Despite the great variety of methods proposed in the literature, the effects of NLOS have not been completely mitigated. Crowded environments and complex geometries scenarios still represent a challenge to overcome.

Finding a good trade-off between the accuracy and the energy consumption of a localization system is an on-going challenge. In particular, energy efficiency is a critical constraint of wearables due to their small form factor and portability requirements, which prevent them from using large batteries. While outdoors, the *de facto* localization system for many wearables is GNSS, indoors there are many competing technologies with varying degrees of localization accuracy and energy efficiency. Widely-available technologies like Wi-Fi and Bluetooth often rely on fluctuating Received Signal Strength (RSS) measurements or imprecise Time-of-Arrival (TOA) estimates, which decreases their localization accuracy. UWB-based localization systems can achieve cm- or dm-level accuracy and have a low energy consumption. However, they are not readily available in most of the wearables already on the market. Future efforts are required to develop accurate localization techniques that can be implemented with low costs and low overhead on small devices.

Location privacy is a major concern of wearable localization, as location information in the hands of non-trustable parties can lead to a disclosure of unwanted private information, identity theft, or decreased safety. Communication privacy and authenticity validation in wearables are also essential, as privacy suggests that an individual keeps personal data as much as possible under control and to share them only with "trusted" devices [402].

Building large-data collection platforms constitutes a Software (SW) engineering challenge, which requires innovation in data analysis and visualization techniques to gain insights into individual and aggregated user patterns, i.e., Spatio-temporal clustering, visual analytics, etc.

Standardization is the most powerful framework to provide fast, secure, and straightforward integration between different devices, components, and systems. Various standards have not been fully adopted in existing localization systems, specifically in indoor localization platforms. For instance, the authors in [403] evaluated indoor localization systems and provided general comments on the International Organization for Standardization (ISO)/International Electrotechnical Commission (IEC) 18305 standard. The authors emphasized the lack of standard evaluation procedures for the customized ILS and Indoor Positioning System (IPS), impeding to be embraced in other environments. However, standardization is not only limited to the evaluation procedures. It is also applicable to positioning technologies, indoor maps, software communication protocols, devices, discovery protocols, among many others.

The ISO/IEC 18305 [404] is an ISO standard devoted to identify and define the most appropriate metrics and scenarios to assess localization and tracking systems. Indeed, many researchers have reported difficulties in comparing the methods with the published results because the evaluation metrics reported differing in the literature (e.g., averaged positioning error, mean squared error, median error, among others). The experimental part and data collection in the literature present significant differences with various evaluation area sizes and strategies to evaluate the method, procedures, and protocols for data collection. Thus, the ISO/IEC 18305 standards can be considered as a guide on how evaluation results should be reported, including aspects on the evaluation area, with special interest indoors. Additionally, some initiatives standardize the evaluation of localization systems through extensive sets of pre-collected data (datasets), providing an evaluation framework that can be reproduced. Localization competitions are also becoming popular in the evaluation as they allow the comparison of real-time localization solutions under the same conditions in challenging areas.

Although some of these standards are available in the literature, most application platforms do not adapt to these standards. It results in non-standards localization platforms that are difficult to integrate with other systems, which is the major challenge for developing indoor localization technology nowadays. As stated in [405], we need a common taxonomy with the related services and protocols, as it is the most relevant missing piece in indoor localization now. The next steps should focus on defining a taxonomy of ILS/IPS, outlining the framework to allow the collaboration of multiple ILS/IPS, and drawing the required standard services and applications in the near future.

4.5. Communication and architectural aspects

Smart wearables need to be interconnected in a heterogeneous manner (i.e., different technologies and devices communicating with each other), battery-operated. They may harvest energy, e.g., from the sun or human motion. They enable various smart functions, which cooperate in a decentralized manner and offer Internet access. Designing efficient D2D-based capabilities is one of the vital unsolved challenges in wearable communications due to the need for heterogeneous, decentralized, low-cost, and low-power architectures. Despite advances in semiconductor technology and energy-efficient system design, overall energy consumption by communications systems is still proliferating. As users' expectations for the networking devices' features and battery life continue to grow, it is imperative to optimize performance and power consumption further. Therefore, the collection, transmission, computation, and storage of data must be addressed consistently in terms of power and/or time.

In dynamic Large Scale Environments (LSEs), where wearables move around while exchanging data, issues related to scalability and interoperability emerge to be carefully addressed. These LSEs rely on Edge/Fog computing architectures to implement the intelligence needed by the proximate devices and improve the quality of service they offer. Edge/Fog architectures require adequate models with a high degree of device autonomy and management. Since such systems typically span over a wide area and include a large number of interacting devices, the aspects of service and object discovery, and reputation assessment require intelligent management. To address these challenges, the development of novel Edge/Fog architectures for D2D to improve wearables' energy efficiency and support massive, heterogeneous, and multi-connectivity devices is required.

4.5.1. In-band/out-band D2D communication

Regarding spectrum usage, D2D communication is primarily classified into in-band and out-band. In in-band D2D communication, both cellular and D2D communications utilize the same spectrum licensed to the network operator, whereas out-band D2D communication operates in an unlicensed frequency band. As pairs of devices are supposed to be in close proximity to establish D2D communication, less transmit power is required than while using longer-range transmissions, which can prolong the devices' battery life [406]. Besides, D2D communication can also result in low-transmission delay and high throughput compared to Base Station (BS)-assisted communication. On the one hand, the use of out-band D2D eliminates the interference between D2D communication and network users, while at the same time, devices have to maintain two active wireless interfaces, which leads to higher energy consumption. On the other hand, in the case of in-band D2D, where devices need only one active interface, the interference poses the main issue. To handle the interference, efficient and easy-to-implement methods are required, which pose a challenging task to the academy.

4.5.2. Packet aggregation

Wearable devices are generally physically close, thus, they perform local end-to-end interactions with traffic that follows similar patterns. In such a scenario, an aggregator node can collect data packets from neighboring devices and then forward them to the final destination employing D2D technology. The advantages of adopting this forwarding approach can be to lessen energy consumption and improve communication performance thanks to a top-notch selection of the aggregator node and a proper setting of its transmission. As shown in [407], using a more robust Modulation and Coding Scheme (MCS) in the uplink can improve the energy-efficiency of communications with small data transmissions by reducing data rate and lowering the transmission power. In [408], the authors propose a strategy where a single device aggregates locally generated machine-type data packets, supplements them with its data, and then transmits them to the BS in order to alleviate the impact of the massive number of Machine-to-Machine (M2M) devices on a cellular system.

4.5.3. Higher cellular system capacity

A dense communication environment poses a challenge from the connection establishment point of view as interference from the devices of neighboring users can make establishing connection difficult [230]. The level flow dynamics of connectivity in wearable devices also add further complexity to this problem. Since interference footprint from a device can be managed by controlling the transmit power, power management [409] approaches can be utilized to minimize the interference and potentially provide more efficient and reliable connectivity.

Generally, D2D communications allow extending the system capacity thanks to data offloading and reuse gain. Freeing up licensed bandwidth through unlicensed D2D communications improves the scalability of the system, thus allowing better management of the resources available for the wearable environment [410]. Furthermore, due to advances in research on methods for the interference management between local D2D communications and the BS, resource allocation in the cell and model selection, it is possible to implement frequency reuse techniques that spur an increase in the network capacity. Finally, the joint utilization of D2D communications and MEC technologies improves cellular networks' computation capacity by the tasks offloading to a nearby D2D device and an Edge node [411].

4.5.4. Group communications

Group communications consist of one-to-many transmissions suitable for scenarios in which the same data must be sent to multiple devices. In wearable technology, performing group communications (also known as multicast) could help tackle energy savings, scalability, and network traffic reduction. Furthermore, to improve the QoS offered to all gadgets, multicast D2D communications can be established towards devices experiencing adverse channel conditions [412]. In this case, the forwarding mechanism requires that a device, chosen as a relay node, after receiving the data directly from the BS, forwards it to a cluster of devices set up using a proper approach. Researchers have proposed many cluster-based multicast transmission methods for D2D communications [413]. Moreover, in the dynamic multi-hop multicast schemes, the optimal number of relays must be appropriately selected by taking into account a trade-off between multicast gain and multi-channel diversity.

4.5.5. Computational offloading

In scenarios with low connectivity opportunities, mobile devices may use local resources on the other devices in close proximity to compute a common task when offloading to remote clouds fails [358]. Using D2D communication, users can improve mobile cloud computing performance in terms of computational acceleration. A significant problem in studying D2D connectivity as an alternative to Mobile Cloud Computing (MCC) is how users can discover and use other mobile devices' computing resources. Since D2D connection is usually intermittent due to user mobility, access schemes need to be carefully designed. The users can make the most of nearby mobile devices' computing resources without spending too much power on device discovery.

4.6. User adoption aspects

The issue of user involvement is especially acute in two areas: medical and industrial. In all other situations, the use of wearable devices is a person's choice. It is often a matter of necessity in the case of medicine and industry. There is a severe risk that pervasive devices, due to their complexity and excessive "intrusiveness", ingenerate unnecessary discomfort feelings and psychological stress in users. Some patients humble themselves in the case of medical examinations since they see a direct connection between the need for monitoring and recovery (or maintaining their condition). Moreover, workers usually do not fully understand the purpose of monitoring in the case of industries [414], and attempts to implement wearable devices in industries often meet with strong resistance from the intended users.

Nonetheless, the information ownership issue generates user distrust of wearable technologies. The privacy reasons suggest an individual to keep personal data as much as possible under control and to share them only with "trusted" devices. The lack of attention to privacy control would imply, for the user, a constant intolerable fear that his sphere is violated and could ultimately lead to a state of depression. In the case of industries, workers are often afraid that the information collected from wearable devices could be used against them as grounds for dismissal or transferred to third parties [415].

Another point directly related to the degree of user involvement is their technical skills. Young people are quick to learn new technologies, while older people, who most often need medical attention, are usually not so good. As a result, they may prefer more traditional technologies and resist new ones, such as wearable devices.

An essential step in overcoming the resistance of users of new technologies is creating detailed and, at the same time, simple instructions that would explain how the device works, what data it collects, and how this data is protected.

Finally, users want to take care of themselves. Sometimes, this means quickly adding sensing, measurement, computation, and communication devices to the platforms already in use. It should be done dynamically and in a "plug-and-play" manner to hide differences in IoT technology, configuration, and data format.

Another issue related to human involvement is the biological safety under radio-frequency radiation. Health concerns attract exploding interests from the research community due to extreme proximity and direct physical contact with the human skin. Moreover, wearable devices are recognized to cause a higher level of Specific Absorption Rate (SAR) [416]. The SAR value is determined when the device is operating at maximum power. The human body absorbs electromagnetic radiation, which causes thermal or non-thermal radiation in the affected tissues. In this regard, it is vital to direct the research towards regulation aspects based on new device types, materials, operated frequencies, and transmit power [214]. For instance, in [417], the exposure amounts in different spectrum bands are investigated. Furthermore, industry bodies should be introduced with the latest regulations to address users' concerns better and promote this new technology.

4.7. Hardware constraints

Several advanced functionalities are being added to wearable devices to enable new services and target new use cases. However, they are still to be executed on tiny and resource-constrained devices. As a result, more features may result in increased energy consumption, which often compromises the quality of the final wearable applications. Hence, energy consumption is considered as one of the most critical challenges in wearable computing [2]. The power alimentation techniques of wearable devices improve with the evolution and the increase of the user demands. For instance, the difficulty in plugging wearable devices into power sources due to their unavailability led to wireless charging techniques. The first commercial devices with integrated wireless charging were cell phones. However, device manufacturers continued deploying these techniques in other devices, such as laptop computers, electric vehicles, and wearables. Although it acts as an alternate solution to regular wired charging and helps remove the charging port from the physical design, the disadvantage of wireless charging is that it needs long charging times [418].

When selecting a wearable device, users consider the energy consumption metric as one of the top selection criteria. This fact motivated the device manufacturers and the research community to explore techniques of extending the battery life of wearable devices, i.e., increasing energy efficiency. The research community identified three main ways for achieving energy efficiency, namely minimizing power consumption, advancing the battery techniques, and energy harvesting. First, the energy consumption of a sensing process in several sensor-based applications may be comparable to, or even greater than, the energy consumption of the radio communication task [419]. Therefore, selecting low-power sensors and using compressed sensing techniques can help minimize the sensing energy consumption, thus, extending the wearable devices' battery lifetime. Second, the choice of compact and long-lasting batteries is a significant design factor in wearables. Li-ion batteries are becoming the most common type in many wearable devices, thanks to their flexible and efficient energy-storage features [420].

While the aforementioned energy efficiency measures can extend wearable devices' battery life, they cannot eliminate the need to recharge and replace the batteries. Consequently, new energy harvesting techniques have been explored to enable the use of self-powered wearable devices. Achieving autonomy by harvesting energy from the environment is especially attractive for wearable systems [421]. The environment's collected energy can be in the form of motion, temperature gradients, light, electromagnetic radiation, etc. These methods include microkinetic energy harvesting systems that use frequencies generated by a human movement to harvest energy [422], powering wearable devices by harvesting solar energy [423], self-powered smart tissue [424], and wireless power transmission for implants [425,426].

However, the development of energy harvesting systems for wearable devices has several problems compared to other traditional devices. These problems are mainly related to wearable devices' internal limitations regarding physical size, weight, and body movement. As a rule, modern energy harvesting efficiency is not high enough to autonomously power wearable devices. Also, the availability of environmental energy is not always guaranteed. Finally, energy harvesting requires integrating several additional hardware components on board, such as environmental energy collectors, additional batteries to store the collected energy, etc., which becomes a challenge when considering a small form factor. Therefore, a significant amount of research is required in this direction so that future wearable devices can continuously generate energy from external sources [427].

Self-powered devices are not considered the last step towards energy-efficient operations of wearables. The circuit technology advances aim to reduce the device power consumption up to keeping them perpetually alive. As a result, a future breakthrough for achieving always-on things in IoT is the concept of zero-energy devices [428]. This concept is based on zero-power sensing, where all the energy needed for the measurement data is generated by the specific physical phenomenon being measured. Therefore, no other power supply sources need to be present in the system. The generation of the energy from the measured phenomenon is performed using two fundamental enablers for zero-energy devices, namely Wireless Energy Transfer (WET) and backscatter technologies.

4.8. Interoperability aspects

While academia, industry, and standardization bodies have shown a substantial interest in developing solutions for the IoWT ecosystem, there are still multiple aspects requiring additional attention, including scalability, mobility, dynamicity, heterogeneity and interoperability, adaptability, security, standards, etc. Among these challenges, *interoperability* is one of the main issues since various components, objects, communication technologies, applications, services, etc., need to seamlessly cooperate and interact with each other to realize the full potential of the automated IoWT systems [429].

Despite the impressive potentialities of such systems, the full integration between IoWT and, e.g., eHealth systems are still far from an actual implementation. Two main factors hinder such an integration. The first issue is focused on the interoperability between eHealth devices and wearables. Reference architectures and protocols devised so far for eHealth and IoWT exhibit many differences. The second one involves managing the potentially numerous and heterogeneous node candidates integrated into the eHealth platforms.

Moreover, *personalization* and *interoperability* represent two cornerstones of eHealth systems [176]. Each patient has their peculiarities: one can be computer literate or not, mostly healthy or seriously ill, more prone or reluctant to accept a given treatment (e.g., due to cultural biases). On the other hand, pathologies have their characteristics, and each one requires specific treatment and monitoring. As a result, it is impossible to devise a single one-fits-all eHealth platform; instead, patients need to rely on various personalized solutions. The only way to economically achieve the required high degree of personalization is to construct eHealth systems based on basic devices with a high technological interoperability level.

Most of the attempts to integrate IoWT and eHealth systems carried out so far aim at achieving full interoperability between eHealth devices and wearables. The main idea is to transport part of the ISO/IEEE 11073-20601 over protocols typically used in the IoT [434] or widely diffused in Consumer Electronic devices [435]. The work [434] also proposes to transport ISO/IEEE 11073-2060 messages over the CoAP [445] with Representational state transfer (REST) API, which has been designed by the Internet Engineering Task Force (IETF) Constrained RESTful Environments (CORE) Working Group [446] also approach to constrained nodes.

CoAP is considered the reference Web transfer protocol to enable the inclusion of the simplest object in the Web. The transport of ISO/IEEE 11073-20601 over CoAP is not straightforward. While communications in CoAP are initiated from a client towards a server, both a manager or a client can initiate a communication in ISO/IEEE 11073-20601. This discrepancy requires the deployment of a CoAP client and a CoAP server on the manager and agents, thus increasing the computational load of devices.

Similarly to [435], the work [447] proposes to transport ISO/IEEE 11073-20601 messages over the UPnP protocol, a technology introduced by the Digital Living Network Alliance (DLNA). This open network architecture enables discovery and control of networked devices and services and is widely deployed in modern Consumer Electronic (CE) devices, such as media servers and smart TV. Besides basic communication features, UPnP also provides management features as a device discovery mechanism that allows applications to opportunistically use the nodes near a patient with no prior knowledge.

In [434,435], the Application Hosting Device (AHD) was chosen as the conjunction point between the Continua architecture and IoT. In other words, this is the device where ISO/IEEE 11073-20601 is mapped onto CoAP/UPnP AHD plays this role because it is the device closest to the patient and powerful enough to run multiple protocols and perform complex operations.

Other proposals in the literature retrofit biometric sensors with CoAP, but are either non-compliant with the continua guidelines or with the ISO/IEEE 11073 standard set [448]. It cannot be considered a real integration with the legacy eHealth system, which will continue to represent and exchange information according to their standards. Therefore, most of the benefits coming from the integration are lost.

Abstracting from the integration of the IoWT and eHealth systems, the work [279] presents the open challenges of IoT interoperability needed to be solved. One of the open challenges is ensuring the interoperability of IoWT applications and solutions from all perspectives such as devices, networks, and others (for more details, see Section 3). In contrast, the current solutions face interoperability from a specific perspective only. This finding highlights the direction for future IoWT adoption. Another area of the research work identified in [279] is the implementation of scalable interoperability solutions able to ensure reliable D2D connectivity [449] between devices with different computational capabilities (e.g., high-end and low-end devices). Moreover, with the enormous current interest in digitalization, the transition toward distributed cloud computing is an inherent part of future 5G and beyond platforms. It is crucial to develop interoperability solutions for different platforms and applications with a high level of flexibility in this context. Finally, it is vital to address interoperability between more than a couple of platforms. Solutions must be realistic and scalable across multiple platforms regardless of the area and domain, scenarios, and even utilized technologies.

To sum it up, seamless and ubiquitous communications are expected to accelerate technological innovation, increase productivity and reliability, and open up new opportunities for IoWT technologies. Therefore, end-to-end solutions for wearable things that offer seamless integration into existing systems and processes are of great concern. Moreover, it is essential to note that weight, size, power, durability, reliability, and ease of use are key considerations in finding solutions for the end-users [450].

Table 6
Summary of the main challenges related to modern wearable technology (sorted alphabetically).

Challenge	Groups	Refs.	Observed existing approach
Appropriate service/DT placement and migration	A, DP	[430]	Utilization of an algorithm for replica placement
		[366]	An algorithm for the optimal migration strategy of services based on dynamic programming
		[367]	A model for resource management based on the regularization technique
		[368]	A framework to design optimal service migration policies based on Markov decision process
Data collection issues	DP, SW	[336,337]	Development and application of a unified, trusted crowdsourcing platforms
Datasets' imbalance	DP	[431]	The application of data augmentation methods for imbalanced datasets and weighting architecture
Energy overheads related to sensing	DP, HW, SW	[419]	Following of the sensing energy consumption minimization strategy
A feeling of constant surveillance	UR	[414,432]	A detailed explanation of the purpose of the monitoring and what is going to be done with the collected data
		[433]	Providing the user with privacy and security of collected data
Inefficient computing resources detection	A, N	[358]	Carefully developed access shames allowing the users to utilize nearby mobile devices' computing resources as much as possible while not wasting too much energy on other devices' discovery
Inefficient data analytics	DP, SW	[338,339]	Application of techniques from the field of statistics and ML
Inefficient switching among resources in hybrid/heterogeneous networks	A, N, HW	[359–361]	Selection and utilization of improved task offloading schemes
Insufficient computing capabilities	A, N, HW	[358]	The use of D2D communication to improve mobile cloud computing's performance
Lack of appropriate data labeling	DP	[340,341]	Application of semi-supervised methods
Lack of direct interoperability between eHealth devices	A, DP	[434]	A system architecture based on IEEE 11073, Constraint Application Protocol (CoAP), and Universal Plug and Play (UPnP)
		[435]	A reference implementation based on Transmission Control Protocol/Internet Protocol (TCP/IP), CoAP
Lack of modern energy harvesting opportunities	HW	[422]	The use of micro-kinetic energy harvesting systems
		[423]	Powering wearables with solar energy harvesting
		[424]]	The application of self-powering smart fabric
		[425,426]	The integration of wireless power transfer option for implantables
		[427]	Continuous power generation from ambient sources
Lack of network resources	A, N	[410]	The application of D2D to extend the system capacity thanks to data offloading and reuse gain
		[411]	The use of D2D-MEC system to improve the computation capacity of the whole system
Problems related to broadcast communications	A, N	[412]	Group communications (multicast transmission)
Limited amount of the available data	DP	[195]	Extension of the available data by applying the data augmentation techniques
Low data quality	DP	[160]	The application of post-processing techniques to improve the quality
Low data resolution	DP	[335]	The utilization of active and passive data collection approaches to increase the resolution
Low QoS indicator	A, N	[413]	Cluster-based multicast transmission methods for D2D communications
Low technical skills	UR	[415]	A detailed guidance and training including seminars and interactive lessons for every age group
		[436,437]	Friendly and responsive customer support
Non-optimized security and privacy enablers	HW, DP, SW	[438]	Content agnostic privacy and encryption protocol eliminating the need for asymmetric encryption
		[393,439]	Integration of lightweight cryptography solutions including more appropriate elliptic curve types or algorithm implementations
		[440]	More efficient utilization of manufacturer-provide System on Chip (SOC)s accelerated for cryptographic primitives execution
		[441]	Finding trade-offs between the primitive and required level of the provided security
Problems of classification, anomaly detection, forecasting problems	DP, SW	[442–444]	The application of ML approaches

A – Architecture; N – Networking; DP – Data Processing; HW – Hardware specific; SW – Software specific; UR – User-related.

4.9. Management/scalability aspects

The IoWT paradigm is rooted in the simple consideration that the space around us is saturated by a multitude of devices connected to the Internet and unequivocally addressable [451]. The devices usually have limited capabilities when considered singularly, but they become capable of very complex operations when a few cooperate, to say it in a motto: *Their number is their strength*.

However, the efficient management of the considerable IoWT devices' number is not straightforward to achieve, and maybe the most prominent factor which hinders the full accomplishment of the IoWT paradigm [452]. Wearables are usually utilized by single users/companies with high mobility patterns. Therefore, it becomes close to impossible to define the number of available nodes in a given area, their capabilities, and the way of their integration to solve a given problem.

The scientific community is only scarcely working on devising proper ways to manage billions of devices, which will populate the forthcoming IoWT [452]. The issue is still open, and very few proposals are focused explicitly on integrating the IoWT in today's networks.

4.10. Section summary

This section outlined the main challenges present in modern and future wearable devices and underlying technologies. The summary of the most significant ones is presented in Table 6.

These challenges are still unresolved because they are extremely complex and limited by various factors locked in small form-factor devices. Current research efforts are fragmentary and very narrow in scope. They focus either on the machine-centric perspective or on the human-centric perspective, which results in a lack of synergy. Solving the challenges described above requires a unique, multidisciplinary, and inter-sectoral approach and a concerted effort of the best experts from all over the world to make progress beyond the state-of-the-art.

5. Review summary

The evolution of modern electronics towards miniaturization paves the way for a relatively young segment of IoT devices – wearables, the ones we carry and wear on us daily. Indeed, the main building block for mass adoption and broad integration of modern wearables is technology, including computation, communication, battery, chip size aspects, among many others. The history of wearables, provided in detail in this paper, is enormous and dates hundreds of years ago, leading to the devices currently surrounding people and soon joining our ecosystems.

As for modern devices, evolving from the first healthcare devices and conventional activity trackers, different wearables are presently found on various parts of our body, mainly depending on the application scenario and data collection/output needs. Wearables of today preliminary communicate via short-range wireless technology, with few exceptions based on infrastructure connectivity. This tendency is mainly due to present battery limitations and the overheads brought by higher power consumption while using longer-range communication technology. Nonetheless, most wearables are still utilized for data collection purposes requiring sophisticated techniques to achieve higher efficiency of the entire data processing life cycle. However, the tight coupling of various systems provided by different vendors is still one of the most significant challenges of wearables due to the lack of good-practices on interoperability and the appropriate standardization in the young IoWT niche.

To summarize, wearable technology is an essential building block in the future ICT systems. It is still in its infancy, and several critical challenges from data acquiring and processing, communications, security, privacy aspects, hardware limitations, and user adoption are still to be addressed. This paper highlights those and provides the readers with an excessive summary of potential solutions to overcome the present literature.

CRediT authorship contribution statement

Aleksandr Ometov: Project administration, Data curation, Visualization, Writing – original draft. **Viktoriia Shubina:** Writing – original draft, Writing – review & editing. **Lucie Klus:** Visualization, Writing – review & editing. **Justyna Skibińska:** Writing – review & editing. **Salwa Saafi:** Writing – review & editing. **Pavel Pascacio:** Writing – review & editing. **Laura Flueratoru:** Writing – review & editing. **Darwin Quezada Gaibor:** Writing – review & editing. **Nadezhda Chukhno:** Writing – review & editing. **Olga Chukhno:** Writing – review & editing. **Asad Ali:** Writing – review & editing. **Asma Channa:** Writing – review & editing. **Ekaterina Svertoka:** Writing – review & editing. **Waleed Bin Qaim:** Writing – review & editing. **Raúl Casanova-Marqués:** Writing – review & editing. **Sylvia Holcer:** Writing – review & editing. **Joaquín Torres-Sospedra:** Writing – review & editing. **Sven Casteleyn:** Writing – review & editing. **Giuseppe Ruggeri:** Writing – review & editing. **Giuseppe Araniti:** Writing – review & editing. **Radim Burget:** Writing – review & editing. **Jiri Hosek:** Writing – review & editing. **Elena Simona Lohan:** Project administration, Writing – review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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List of Acronyms

3G The Third Generation Cellular Network Technology
3GPP The 3rd Generation Partnership Project
5G The Fifth Generation Cellular Network Technology
A-WEAR A Network for Dynamic Wearable Applications with Privacy Constraints
AAFT Adjusted Fourier Transform
ACES Asynchronous Coded Electronic Skin
AHD Application Hosting Device
AHL Asymmetric Hearing Loss
AOA Angle of Arrival
AI Artificial Intelligence
ALS Amyotrophic Lateral Sclerosis
API Application Programming Interface
AR Augmented Reality
ATM Automated Teller Machine
BAN Body Area Network
BLE Bluetooth Low Energy
BS Base Station
BLSTM Bidirectional Long Short-Term Memory
CAGR Compound Annual Growth Rate
CE Consumer Electronic
CES Consumer Electronics Show
CSI Channel State Information
CHF congestive heart failure
CoAP Constraint Application Protocol
CORE Constrained RESTful Environments
CNN Convolutional Neural Network
CH Cluster Head
D2D Device-to-Device
DLNA Digital Living Network Alliance
DHKE Diffie-Hellman Key Exchange
DT Digital Twin
DTW Dynamic Time Warping
ECG Electrocardiogram
EEG Electroencephalogram
FPV First-person view
eMTC enhanced Machine Type Communication
GNSS Global Navigation Satellite System
GLONASS Global Navigation Satellite System
GPRS General Packet Radio Services
GDPR General Data Protection Regulation
GPS Global Positioning System
GRU Gated Recurrent Units
H2H Human-to-Human interaction
HAR Human Activity Recognition
HMD Head-Mounted Display
HRD Health Recording Devices
HW Hardware
HC-RAN Heterogeneous Cloud Radio Access Network
HCI Human-Computer Interaction
IAAFT Iterated Adjusted Fourier Transform
ICD Industrial Clothing Division

ICT Information and Communications Technology
IDDS Insertable Drug Deliverables Systems
IEEE Institute of Electrical and Electronics Engineers
IETF Internet Engineering Task Force
IF Interface
IIoT Industrial Internet of Things
ILS Indoor Location Systems
IoT Internet of Things
IoWT Internet of Wearable Things
ITB Inside-the-body
IPS Indoor Positioning System
IEC International Electrotechnical Commission
IP Ingress Protection Code
IR Identifiable Infrared
ISM Industrial, Scientific, and Medical
ISO International Organization for Standardization
KARMA Knowledge-based Augmented Reality for Maintenance Assistance
LAN Local Area Network
LBS Location-Based Service
LSI Large-Scale Integration
LED Light-emitting diode
LPWA Low-Power Wide Area
LPWAN Low-Power Wide Area Network (protocols)
LSE Large Scale Environment
LSTM Long Short-Term Memory
LTE Long Term Evolution
LoRa Long Range LPWAN protocol
LOS Line-of-Sight
MAC Medium Access Control
M2M Machine-to-Machine
MCC Mobile Cloud Computing
MCS Modulation and Coding Scheme
MEC Multi-Access Edge Computing (formely Mobile Edge Computing)
mMTC Massive Machine Type Communications
mmWave Millimeter Wave
MR Mixed Reality
MRI Magnetic Resonance Imaging
MS Multiple Sclerosis
MTC Machine Type Communications
MLP Multilayer Perceptron
ML Machine Learning
MIMO Multiple Input Multiple Output
MWC Mobile WOrld Congress
NB-IoT Narrowband Internet of Things
NFC Near Field Communication
NLOS Non-Line-of-Sight
OGC Open Geospatial Consortium
OS Operating System
P2P Peer-to-Peer
PAN Personal Area Network
POA Phase of Arrival
PoW Proof of Work
PDA personal digital assistant
QoS Quality of Service
RAM Random-access memory
RAN Radio Access Network
RAT Radio Access Technology
REST Representational state transfer
RF Radio Frequency
RC Remote control
RFID Radio Frequency Identification
RNSS Regional Navigation Satellite Systems
RSS Received Signal Strength
SAR Specific Absorption Rate
SDN Software-Defined Networks
SIM subscriber identification module
SIoT Social Internet of Things
SOC System on Chip
SSD single-sided deafness
SW Software
SW Software
TCP/IP Transmission Control Protocol/Internet Protocol
THz Terahertz
TOA Time-of-Arrival
UPnP Universal Plug and Play
UWB Ultra-Wide Band
VLC Visible Light Communications
VR Virtual reality
WAN Wide Area Network
WBAN Wireless Body Area Network
WPAN Wireless Personal Area Network
WSN Wireless Sensor Network
WET Wireless Energy Transfer
Wi-Fi Wireless Fidelity
WiGig Wireless Gigabit Alliance (WiFi at 60 GHz)
WLAN Wireless Local Area Network
XR eXtended reality

Appendix. Description of the wearable devices' dataset

During the preparation of this survey, our team has analyzed the market and exiting research projects, which resulted in the dataset allowing for easy analysis of the available wearable devices. The most recent version of the dataset is available via Zenodo repository https://zenodo.org/record/4575153. As of the paper submission date, it provides the data about 224 wearable devices.

In particular, it consists of the following fields (some fields could be empty due to the unavailability of the module):

- **Device** – name of the wearable on the market or project title;
- **Location type** – data on the wearablity, based on the proposed classification;
- **Application type** based on the proposed classification;
- **Device type** based on the proposed classification;
- **Hi/low end** – type of the device according to its' functionality;
- **Prototype** or availability on the market;
- **Energy-related information** – information either on power supply or on the battery type;
- **CPU** – information about the processor;
- **GPU** – information about the graphical card;
- **Camera** – information about the camera(s);
- **Cellular** – information about the cellular module and technology;
- **WiFi** – information about the WiFi module and technology;
- **Bluetooth** – information about Bluetooth module and, optionally, version;
- **RFID** – information about RFID module;
- **Other connectivity** – the list of other connectivity options present on the device;
- **GNSS** – information about conventional positioning systems;
- **RAM** – information about integrated RAM;

- **Storage** – information about available internal storage or slots available for external memory stick;
- **Display** – information about the graphical output interface;
- **Audio output** – information about audio output devices;
- **Mic** – presence of audio input interface;
- **Release** – first release date or year;
- **Price $** – market price as of 2020;
- **Luxury** – information if the device could be considered as a luxury accessories;
- **Activity tracking** – presence of the activity tracking feature with details;
- **Sensors** – list of the sensors and actuators integrated in the device;
- **Description** (optional) – short description of the device;
- **Other comments** – additional notes on the device;
- **Link** – example link with the device information.

An example of one entry could be found in the following listing:

```
[
  {
 "Device": "Focals by North",
 "Location type": "Head_mounted",
 "Application type": "Eyewear",
 "Device type": "AR",
 "Hi or low end": "high",
 "Prototype": "yes",
 "Energy−related information": "700 mAh/18 hours",
 "CPU": "Qualcomm APQ8009w",
 "GPU": "n/a",
 "Camera": "yes",
 "Cellular": "no",
 "WiFi": "no",
 "Bluetooth": "yes",
 "RFID": "no",
 "Other connectivity": "no",
 "GNSS": "no",
 "RAM": "n/a",
 "Storage": "n/a",
 "Display": "yes",
 "Audio output": "yes",
 "Mic": "yes",
 "Release": "n/a",
 "Price $": "n/a",
 "Lyxury": "yes",
 "Acitivity tracking": "yes",
 "Sensors": "9−axis IMU, Ambient Light Sensor,
                              Proximity sensor",
 "Description": "Smart AR glasses. Could be
        used as handsfree and with assistants.",
 "Other comments": "IP55",
 "Link": "https://www.bynorth.com/tech"
 },
<...>
]
```

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