CHAPTER

2 Biosensors and Internet of Things in smart healthcare applications: challenges and opportunities

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Chapter Outline

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2.1 Introduction

As the global population ages, several disorders, diseases, and impairments are becoming prevalent with significant financial and social implications. The prevention and appropriate handling of such conditions will benefit both individuals and national healthcare systems. Smart information and communications technology (ICT) solutions can provide benefits such as improving the quality of life and supporting independent living of the elderly and other groups with chronic or acute conditions.

Biosensors are complete analytical devices composed of a receptor, an active biological factor that can be an enzyme, antibody or similar, coupled with a transducer and are able to detect the existence of a particular analyte. They are continuous sources of biological data and when integrated in a smart analytics framework, they can provide useful information about a person's condition. Smart biosensors in health capitalize on recent advances in microtechnology and wireless communication in order to collect and transmit information and, in conjunction with actuators, are able to provide better monitoring and treatment. For example, wearable biosensors provide vital signs monitoring for everyone, including patients, children, and the elderly, and are very effective in health risk prevention and control.

The use of smart biosensors can benefit people that require medical support or care, as well as for older adults, who face a gradual degradation of their motor, cognitive, and other skills due to aging. Smart biosensors can also help individuals exposed to harsh working environments, or who perform stressful tasks or tasks that induce health risks. The continuous monitoring of biosignals in combination with environmental sensing allows smart systems to promote a reactive living and working environment that provides appropriate and timely recommendations, acts preventively, and mitigates health risks.

The long list of biosensor applications [1,2] includes, among others, helmets for treating depression through electrical pulses and smart clothes (e.g., socks, shoes, t-shirts, and smart vests) that noninvasively collect and transmit vital signs and integrate well with the concept of a smart house or a smart working environment.

Several technological and societal challenges pose barriers to the widespread adoption and deployment of smart biosensor applications. These barriers relate primarily to the interoperability and expandability of the overall solution. Moreover, the ability to collect and process large amounts of data from heterogeneous sensors, as well as the ability to provide high-level data analytics and extract knowledge, ought to overcome all technological barriers. This ability to collect and analyze data will support the development of solutions and provide evidence supporting the effectiveness of personalized interventions and recommendations that will promote user trust. This chapter aims to highlight challenges and opportunities pertaining to the application of smart biosensors in healthcare and to present the main building blocks required for such applications. Finally, three state of the art solutions leveraging smart sensors in this context are presented.

The chapter is further structured as follows. Section 2.2 highlights health challenges faced by the elderly, older workers, and infants, as well as the social and financial implications associated with these challenges. Section 2.3 presents the main challenges and opportunities for technology-enabled care (TEC). Section 2.4 describes the building blocks for the Internet of Things (IoT) and the Internet of Medical Things (IoMT) in health and well-being applications, which are smart environment enablers, back end enablers for personalized recommendations, plus security and privacy enablers. Section 2.5 presents three state of the art smart healthcare applications to address challenges in living and working environments.

2.2 Health challenges for the elderly, older workers, and infants

According to HelpAge International,[1] by the year 2050, one in five people will be over 60. Among the 10 most prevalent health challenges that lead elderly people to physical injuries and affect their ability to have a healthy and independent life [3] are the following:

- *Hearing loss (HL)*: HL is one of the most prevalent chronic conditions in older adults [4] and affects one-third of people ages 65–74, as well as nearly half of those older than 75. HL increases the risk of cognitive decline and depression and can lead to social isolation.
- *Cardiovascular diseases (CVDs)*: Hypertension, ischemic heart disease, and heart failure are the primary causes of death globally (31% in 2016, 85% of which were from ischemic heart disease and stroke) [5]. CVDs affect many aspects of life for elderly adults including their physical, social, and emotional status.
- *Cognitive impairments (CIs)*: CIs affect the ability of people to think, learn, and remember. Dementia is the most common issue with approximately 47.5 million cases worldwide and a prediction to triple by 2050. Dementia has high comorbidity with heart failure among the elderly and affects several cognitive domains including executive and motor function [6].
- *Mental health (MH) issues*: MH issues affect a significant proportion of the older population (e.g., depression at 7%, anxiety disorders at 3.8%, substance

[1] www.helpage.org/resources/ageing-data/global-ageing-statistics/

use problems at nearly 1%, self-harm attempts underlie 25% of elderly deaths) and in some cases have an impact on physical health. Adults with other health conditions (e.g., heart disease) have a higher risk for MH issues.

- *Balance disorders (BDs)*: BDs are disturbances in coordination that make someone feel unsteady, dizzy, or have a sensation of movement. This progressive, age-related loss of sensory functions and inability to control body movements frequently lead to falls, physical injury, and death (one elderly person dies from falling every 29 minutes [7]). Frailty is quite prevalent among elderly people. The prevalence ranges from 33% to 88% depending on how frailty is defined and steadily increases with age. Frailty and other progressive disorders increase the risk for the elderly and negatively affect their quality of life [8].

Because health problems increase with age and the age limits for retirement continue to increase, more employees are likely to develop health problems while still at work. Changes in physical abilities (e.g., balance, mobility, dexterity, stature, strength, and aerobic power) can result in a reduced tolerance of physical work and declines in motor skills (e.g., difficulty maintaining coordination, loss of flexibility), rendering tasks that require fine manipulation harder for older workers. Finally, changes in cognitive abilities (e.g., declines in episodic memory, executive functioning, and attentional control) reduce task performance and affect work capacity [9]. Conversely, cumulative exposure to demanding work can have a significant impact on health and functional abilities, wellness at work, and productivity. Arduous working conditions (e.g., exposure to extreme temperatures, dangerous substances, or noise) have a major influence on the risk of developing work-related ill-health (e.g., illness, stress, fatigue). When work environments require workers to exert intense physical effort, even occasionally, it is important to keep workers safe and healthy so as to increase their resilience and avoid injury risks [10].

On the opposite end of the age scale, various pathological conditions can arise during the first year of life in infants, which call for immediate detection and intervention. Parents cannot always identify the signs of pathology that specific movements and sounds of an infant indicate. According to the World Health Organization[2] a child is at the highest risk of dying in the first 28 days of life, while at home. This risk is especially high when neonates are discharged early from the hospital. Current countermeasures include postnatal care plans built around home visits by healthcare professionals. Many pathological situations can occur during an infant's sleep that can potentially be harmful to the infant's health if not detected promptly: breathing disorders, vomiting, arrhythmias, epileptic and febrile convulsions, high fever, and sleep disorders including sudden infant death syndrome (ranked in order of life-threatening risk).

[2] https://www.who.int/news-room/fact-sheets/detail/newborns-reducing-mortality

2.3 Challenges and opportunities for technology-enabled care

2.3.1 Low-cost technology

The explosive growth of IoT [11] and associated technologies has placed downward pressure on the cost of associated hardware and software [2]. Building successful low-cost TEC solutions depends on a number of factors related to sensors or the network itself. Sensors must have: (1) low power consumption for prolonging battery life; (2) physical characteristics that provide unobtrusiveness; (3) robustness to minimize maintenance; (4) wireless connectivity to facilitate networking using widely accepted standards; and (5) data preprocessing capabilities to reduce computational load on gateways and the cloud. The network itself must support: (1) the deployment and management of a large number of low-cost sensors and (2) high processing speed and portability to enable better care at lower cost.

2.3.2 Modular, interoperable, expandable solutions

The integration of a large number of heterogeneous smart objects that use different communication technologies (e.g., Bluetooth, RFID, Zigbee, 802.11, 802.15.4), run a variety of often proprietary protocols and applications, and have limited exposed interfaces, requires careful engineering actions that will interconnect IoT devices in a network and will build realistic and useful novel IoT solutions [12]. Many surveys highlight that vendor lock-in and complicated security and management processes hinder the broader adoption of IoT technologies [13]. Aiming to alleviate the interoperability issues, various emerging IoT platforms are either domain-specific (e.g., UniversAAL[3]) or general purpose (e.g., FI-WARE,[4] GoogleApp engine[5]). Thus, developers rely on existing platforms and their services, and future platforms must be interoperable with the existing ones. Moreover, various standardized "IoT communication protocols" have been proposed, aiming to address the interoperability and fragmentation issues. The MQ Telemetry Transport (MQTT[6]) is one such machine-to-machine (M2M) connectivity protocol, which was recently standardized by OASIS (also standardized as ISO/IEC 20922), and already applied in various domains including eHealth [14] and smart homes [15]. The OASIS standard devices profile for web services (DPWS) [16] supports the interaction with resource-constrained devices and has been studied extensively in many areas, including eHealth and smart homes [17]. The IETF standard constrained application protocol (CoAP) [18] offers an

[3] http://www.universaal.info

[4] http://www.fi-ware.org

[5] https://cloud.google.com/appengine/

[6] https://docs.oasis-open.org/mqtt/mqtt/v5.0/mqtt-v5.0.html

alternative web transfer protocol that allows the integration of constrained IoT nodes through lightweight interactions.

2.3.3 Big data and machine learning

With environmental sensors and wearable devices, smart healthcare platforms can continuously monitor the health status and activities of patients and the elderly, as well as the safety and security of the environment [19,20]. This continuous flow of data in combination with individual's medical histories, can support personalized diagnosis and assistance and can automate important tasks, such as medical data archiving and evaluation of the effectiveness of medical interventions. Recent advances in artificial intelligence (AI) and big data processing technologies have allowed the implementation of highly reliable, accurate, and robust infrastructures for data recording and processing [21].

The analysis of data from wearable devices is led by decision-making process requirements, which define the data to be collected and extracted in support of intelligent decision-making. To support intelligent decision-making, the following requirements must be considered: (1) modular and interoperable data ingestion in which devices from different manufacturers contribute to a common data model, (2) parallelization and data stream processing in all steps from data acquisition to storage and processing, (3) use of data analytics and AI to support automatic monitoring and decision-making, (4) privacy-aware data processing to ensure consistent data encryption, database security, as well as secured communication channels.

2.3.4 Security and privacy

Two main issues regarding security and privacy of relevant applications are the complex interaction schemes that take place during typical, everyday use of smart healthcare solutions (e.g., patients/users with their caregivers/medical professionals), along with the private/sensitive nature of the handled data. These factors necessitate the integration of strong security and privacy provisions, including seamless authentication and authorization services, for the protection of the framework's M2M and machine-to-human (M2H) interactions [21]. IoT devices have been designed mainly considering low-cost, low-energy usage, ease of setup and use, and interconnection, but not security. Since health monitoring systems or even smart homes and workplaces may include sensitive assets, it is important to protect them from malicious attackers.

The below define a set of security and privacy risks and considerations:

- Small, low-cost, interconnected devices have immature security functions.
- Low processing capabilities of the network require computationally intensive real-time tasks (e.g., condition reasoning) to be moved to the cloud.

- Secure communication within the smart home uses a range of protocols (WiFi, Bluetooth, NFC, ZigBee, and others) that may open various exploits.
- Privacy protection systems (e.g., smart home sensors) generate a large amount of highly personal data and metadata.
- Consent for secure sharing of anonymized information is necessary.
- The physical security of a smart home is linked to the safety of sensitive systems for the occupants' healthcare.
- Communications with the back end processing systems must be secure.
- Secure and privacy-preserving interactions (communication, processing, storage) with third parties (hospitals, clinics, etc.), their data and metadata.
- Authentication, authorization, and accounting mechanisms must be tailored to all actors (from elderly and clinical experts to sensors and back end systems).
- Reliability and availability of information from back end databases and real-time data streams must be guaranteed.

The information sources to be protected encompass data from smart devices, including raw data, logs, metadata (headers, content type, dates, etc.), events (alerts, warnings, errors, etc.), rules, settings and preferences (which may disclose information about the end user's conditions), updates to and from smart devices, postprocessed data, and interactions of the smart home with the back end cloud, as well as interactions of the back end cloud with various healthcare service providers. All adopted security and privacy mechanisms must be tailored to the above requirements. A key characteristic of these mechanisms will be their capability to adapt in real time to a variety of usage requirements (e.g., context, privacy preferences, risk profile, and other parameters).

2.4 Internet of Things and Internet of Medical Things building blocks for health and well-being applications

2.4.1 Smart environment enablers

2.4.1.1 Wearable and assistive medical devices

A basic component of a smart solution for health is a wireless sensor network that obtains automated, continuous, and real-time measurements of physiological signals and performs limited data processing and functions. Vital signs, such as heart rate, heart rate variability, body temperature, skin conductance, respiration rate, blood pressure, blood glucose, oxygen saturation, as well as activity related signals can be captured and analyzed using appropriately selected sensors that can be placed over clothes or directly on the body. Another physiological measurements that can be recorded is the hearing response, which is supported by hearing aids. Current state of the art technology in the aforementioned sensors lacks multiparameter systems for the concurrent monitoring of multiple physiological

Table 2.1 Physiological measurement solutions in the Internet of Things era.

Physiological measurement	Sensor type	Data provided
Heart rate	PPG	Raw
Blood pressure	Pressure sensor	Raw
Blood glucose	POC	Raw
Respiration rate	Sensitive stretch sensor	Raw
Oxygen saturation	PPG	Raw
Body temperature	Thermocouple	Raw
Skin conductance and temperature	GSR	Raw
Activity	IMU	Raw, aggregated
Sympathetic nervous system activity	GSR	Raw
Hearing response	—	Raw, aggregated

GSR, *Galvanic skin response;* PPG, *photoplethysmography;* POC, *point-of-care;* IMU, *inertial measurement unit.*

measurements. On the other hand, the utilization of separate sensors is not practical and may cause inconvenience and obtrusive operation for the end users.

Physiological signals from the human body can be measured with various sensor technologies [22], some of which are depicted in Table 2.1. The heart rate, which has become a routine measurement, can be easily extracted from photoplethysmography (PPG) signals. Blood pressure derives from inflatable cuffs accompanied with a stethoscope. The evolution of this medical device resulted in an integrated smart pressure sensor [23]. Moreover, blood oxygen saturation, a valuable vital parameter, can now be easily measured through the exploitation of PPG technology. PPG is a biophotonic technology using two different light wavelengths [24]. The basic type of sensors in skin sweat monitoring is epidermal galvanic skin response (GSR) sensor. Respiration rate is used to detect stress and potential hypoxia [25].

More recently, wearable devices that can infer the human physical activity have gained popularity. Such devices often incorporate inertial measurement unit (IMU), global positioning systems (GPS), PPG sensors, ECG leads, and sophisticated firmware capable of high quality and continuous biosignal monitoring [26]. Finally, sympathetic nervous system activity can be captured using electrodermal activity sensors, which offer information about alterations in the central nervous system. Assessment of these alterations leads to indicators of the emotional condition of the subject [27]. The abovementioned sensors can be integrated into wearable devices specifically designed to extract raw, aggregated, or both types of data and collectively compose a smart IoT ecosystem.

Considering the above landscape, a smart healthcare solution must be able to integrate physiological measurements, such as those reported above, aggregate (and preprocess, if necessary), and transmit them to a back end cloud platform. There, huge amounts of raw and aggregated data can be analyzed through advanced big data analytics in order to understand behavioral activity, detect probable risks, and provide adequate interventions.

2.4.1.2 Mobile devices

Mobile devices are an integral part of smart healthcare solutions. They are the near perfect interface to actively gather self-reported data from individuals. Additionally, they contain a vast array of embedded sensors and features for collecting a large variety of data, both actively and passively, which can be used to infer information regarding a subject's current health or mental state. Behavioral signals such as speech, facial expression, and gaze can also be collected through the cameras and microphones embedded in all consumer smartphones and tablets. Furthermore, mobile devices offer temporary storage and the means to remotely transmit this information. They also represent a straightforward solution for the intermediate storage of health and wellness data collected from wearable and other IoT devices before transmission to a back end cloud platform for analysis [28]. However, as already pointed out in the previous section, this transmission represents a potential security risk and can quickly drain the limited power available to these devices. In addition to functioning as storage, transmission, and potentially processing devices, smartphones represent a new source of health and wellness information. In particular, the shift to mobile devices, smartphones, and tablets as core communication platforms, has resulted in a new source of data known as digital-trace information. This data stream is generated implicitly through smartphone usage and can be collected passively and unobtrusively (without specific user interaction) by the use of specially designed apps. One such app is RADAR-BASE, which runs as a background process and automatically collects and transmits this information for analysis and predictive monitoring [29]. Implicit trace information gathered from smartphones includes social activities as monitored via call and message logs, social media usage, or Bluetooth connectivity, and activity levels as inferred from embedded sensors or GPS data. Ambient noise and light levels, screen time, and application usage can also be easily collected.

A growing area of research in smart healthcare solutions is the embedding of AI technologies directly into mobile devices. However, considering that a modern deep neural network can have millions of hyperparameters to tune, the computational demands associated with these technologies are very high, potentially requiring hundreds of megabytes. In several cases they also need substantial data movement to support their operation, thus constituing a highly nontrivial process. One growing research direction within neural networks is the development of approaches that can import large networks and optimize them until they are executable on a low resource smart device [30]. Other methods are aimed at lowering the memory footprint and computational complexity of AI technologies while maintaining reasonable accuracy. Developing low resource networks increases the likelihood of smart systems being able to run offline, increasing user privacy and reducing energy consumption concerns associated with transmission bandwidth, all of which are core considerations for a robust smart healthcare solution.

2.4.1.3 Environmental monitoring and Internet of Things platforms

Environmental monitoring encompasses a broad variety of IoT applications that involve online monitoring of environmental parameters such as temperature, humidity, noise levels, air pollutant concentrations, etc., which affect people's safety and well-being [31]. The measured parameters are collected through dedicated gateways by an IoT platform for monitoring and analytics.

The most popular IoT platforms for use as secure gateways are AGILE IoT, Eclipse Kura, and HomeAssistant.[7] They are open source, feature ready-to-use field protocols, and support wireless and wired IoT networking technologies such as WiFi, Bluetooth Low Energy (BLE), ZigBee, Z-Wave. Technology advancements in Bluetooth low energy, make BLE devices suitable for the development of IoT networks, combined with power harvesting elements and mobile gateways [32]. For publishing data and events to IoT cloud platforms, MQTT connectivity is an option available to all platforms. Every platform uses its own authentication system (OAuth2, multi factor authentication, etc.). For secure access, HTTP SSL/TLS protocols and MQTT connectivity ensure the privacy of established connections.

AGILE IoT builds a modular and adaptive gateway for IoT devices that supports interoperability of devices and data. Modular hardware solutions that adopt all communication protocols in combination with the appropriate software components that offer smart services (data management on the gateway, intuitive interface for device management, etc.) allow fast prototyping of extensible solutions. Eclipse Kura is an extensible open source IoT Edge Framework that offers application programming interface (API) access to the IoT gateways (I2C, GPS, GPIOs, serial ports, etc.). HomeAssistant is an open source IoT platform with hundreds of built-in components for connectivity with off-the-shelf sensors, providing an easy framework for importing more devices and a mobile-friendly interface for setting up automation rules and monitoring devices.

2.4.1.4 Camera-based monitoring of humans

Despite not yet being widely adopted in IoT frameworks, visual sensing using cameras has several attractive advantages over other sensing modalities. These advantages stem from the fact that visual sensing can support the extraction of detailed context information from a scene, while being passive, low cost, and nonintrusive. Context awareness facilitates a better understanding of the activities/actions, health, and risks faced by a subject being monitored by detecting behavior patterns and supporting more precise inferences about the subject's situation and environment. Many systems rely by design on the extraction of low-level context information, such as the location of users, derived by nonvisual sensors and technologies. However, in cases with more elaborate monitoring

[7] http://agile-iot.eu, https://www.eclipse.org/kura and https://www.home-assistant.io

requirements, for example, when one needs to extract higher level information such as behavioral patterns and the subject's activity, or when the environment is occupied by multiple persons or contains certain materials such as metal parts that may interfere with localization radio signals, visual information from camera sensors can provide richer and more precise information. However, in an IoT camera-based monitoring system, there are security and privacy risks that relate to the transmission of images away from the imaging sensor for processing. Therefore it is preferable to move the application of security and privacy protection closer to the sensor, enhancing control of data privacy and simultaneously accommodating key concerns among users regarding privacy violations.

Beyond privacy issues, considering that human behavior in daily activities is complex and highly diverse, monitoring such activities presents significant challenges. As outlined in [33] these challenges are: (1) recognizing concurrent activities (i.e., individuals performing several activities simultaneously), (2) recognizing interleaved activities (i.e., activities that are overlapped with others), (3) ambiguity of interpretation (i.e., similar actions may be interpreted differently depending on the context), and (4) support of multiple users (i.e., recognize activities performed in parallel by many users in a group). Human behavior is characterized by varying time frames and levels of semantics [34]. In addition to the above, robustness to variations in real-world indoor and outdoor environments is affected by scene- and image-dependent factors, such as variations in the performance of actions, background clutter, occlusions, lighting conditions, and camera sensor selection and placement [35].

With the advent of low-cost, real-time dense depth cameras such as the Kinect,[8] numerous important approaches to action recognition and tracking problems have emerged, pushing the state of the art significantly forward [36]. Nevertheless, and despite the fairly accurate performance of state of the art algorithms in controlled or semicontrolled settings, coping with complex, realistic scenarios exposes the limits of these algorithms, particularly effective handling of longer duration occlusions, which remains an unsolved problem in most current approaches [37]. Lastly, such approaches suffer from natural light interference and limited range, and hence are restricted to indoor environments. On the other hand, passive stereo cameras have a wider range of application, as they can operate in sunlight and their field of view can be adjusted by using different cameras, lenses, or baselines.

Apart from spatial ambiguities related to human body segmentation in complex scenes, ambiguities in the temporal domain may also affect action recognition. These are easily resolved with repetitive actions, but they may greatly affect the detection of nonrepetitive actions such as pulling, pushing, or lifting an object. Moreover, performance may degrade in case of domain shift problems, for instance when the scale and shape of the human action are inconsistent with those of training data. Empirical results suggest [38] that convolutional neural network

[8] https://www.xbox.com/en-US/kinect

(CNN)-based algorithms are able to learn similar features between different actors performing the same action (i.e., performance nuance). However, in many real-world problems (e.g., surveillance scenarios), it is not possible to provide massive amounts of training data nor avail enough time for training. Thus, there is a need for algorithms that can work reliably in real time with moderate amounts of data and progressively improve their confidence as more data is learned, ideally in an unsupervised fashion.

2.4.2 Back end enablers for personalized recommendations

2.4.2.1 *Knowledge abstraction for user profiling and temporal reasoning*

In order to reduce predictable acute health episodes, a system should focus on eliminating complications, preventive disease management, and timely detection of anomalies based on past events. However, a characteristic of ordinary computerized healthcare systems is the limitation of user participation in the decisions of the system. User-centered design has been recently adopted as a methodological tool to inform the development of modern health technology systems. Capitalizing on the use of IoT technologies and analytics, modern systems are able to infer hidden patient information and their own risk-related parameters. Constant monitoring of incoming data can be used to trigger warnings based on the identification or prediction of user-independent abnormal parameter values or the identification of crucial deviations from a patient's data profile, which may indicate the increase of a risk. Moreover, exploitation of past data is important for the delivery of personalized treatment based on predictive modeling techniques that will determine the expected treatment response for a certain patient. Still, the comparison between past and current data, which are frequently stored in the form of time series, is not straightforward. Accordingly, it is often necessary to develop abstracted pictures of current and past events, which are contrasted to reveal abnormalities. Dimensionality reduction is commonly used as an approach to develop simplified representations of the different cases (data sequences) and similarity-based comparisons between them to support time series retrieval and decision-making [39]. In recent years, temporal abstraction (TA) has been used as a method to derive high-level concepts from time stamped data [40]. The idea behind TA is to move from a point-based to an interval-based representation of data, which effectively summarizes the data into meaningful parts that are interpretable by the users of the system [41]. The evidence arising from the comparison of different cases is fed into decision models to identify and suggest interventions that either prevent the occurrence of risks or reduce their effect on patient health.

The use of big data analytics and the ease of aggregating and synthesizing anonymous patient clinical records facilitates the creation of custom cohorts and metrics to extract knowledge that can be transferred and applied across different patients and can be a valuable service to third parties [42]. Interestingly, besides building accurate models of disease progression and providing personalized medicine in clinical practice, big data analytics facilitates the integration of medical data with wearable devices and IoT smart sensors. These devices provide information on supplementary behavioral determinants of health and may crucially support the analysis of potential public health policies regarding such interventions at the regional, national, and international levels [43].

2.4.2.2 Context-aware recommendations

The most interactive part of a smart medical care solution based on biosensors emerges when the system recommends actions to the end user based on the information collected by the sensor ecosystem. When developing a recommendation system for a specific purpose, such as the improvement of physical or mental status, it is important to consider what actions to recommend and at which moment they should be addressed to the user. This defines the concept of context-aware recommendation systems (CARS), which take into account the user spatiotemporal environment, as well as other conditions such as the user status (standing, walking, driving) or physical (tired or energetic) and psychological (happy or sad) conditions. Sensors can be used to detect user context [44] and are the backbone of CARS that support health and medical care. For example, Casino et al. [45] propose a CARS that takes into account the health information of citizens and their preferences, combines them with the real-time information about weather and air conditions collected from smart city sensors, and recommends personalized path alternatives that fit each end user profile. The "Motivate" CAR system [46] used several recommendations (e.g., take a break from work, stretch, walk, cycle to a park, go to a museum) that promote social, physical, and mental balance and considered various context parameters including location, user agenda, weather, user profile, and time. "Let's exercise" [47] is another CARS that recommends physical activities. Additional approaches for motivating older people to engage in social and physical activities are presented in Ref. [48], which also proposes a CARS for suggesting social and other events that match user profiles. Biosensors can take CARS to the next level by introducing an additional context, the psychological. The detection of stress and arousal can improve the recommendation timing and increase their acceptance rate.

2.4.3 Security and privacy enablers

Basic security tasks such as mutual authentication, encryption, and data integrity remain challenging in IoT. Encryption using elliptic curves and signatures has been shown to be possible on embedded devices but may not be possible on every sensor or actuator [49]. Confidentiality and integrity protection mechanisms also require strong authentication and authorization mechanisms. This requires assigning an identity to sensors and actuators (i.e., a sensor must store some secret to authenticate to a field device). In the past this was, for example, solved with a second channel and user involvement [50] or using certificates [51]. However, all these solutions lack scalability and support for dynamic, unobtrusive smart environments. Concerning security and privacy at the back end, because smart healthcare applications require distribution and processing of sensitive data, they will need to adopt new distributed and/or collaborative paradigms of cloud computing. The obfuscation and anonymization of uploaded data [52] is a simple technique to prevent sensitive information leakage; however, this technique affects the data and makes it unusable for other applications. Fully homomorphic encryption [53], privacy-preserving encryption [54], and attribute-based encryption have been proposed for encrypting sensitive user data without limiting the functionality of cloud applications. However, cryptography alone cannot sufficiently preserve user privacy and thus other forms of privacy enforcement must be employed [55], such as proper identity and authorization management by specifying and enforcing security, access control, and privacy policies. Indeed, an ENISA report (ENISA, 10) on security and resilience of e-health infrastructures and services identifies access control as a very significant priority in securing applications. Among the studied authorization schemes proposed for systems with different requirements and properties, a cross-platform solution that meets the requirements of all types of embedded systems and provides interoperability is the eXtensible Access Control Markup Language (XACML) [56]), the de facto standard for specifying and evaluating access control policies [57]. Also supporting XACML extension are its privacy-aware features [58].

Another important aspect related to the above and which raises significant concerns is the interplay between machine learning techniques and privacy. More specifically, there is a recent trend to design machine learning models that are trained from IoT data, which raises many privacy concerns and ethical issues. When the data used to train the models is comprised of unfiltered data from the real world, there is the risk of learning the respective behaviors that exist in the data, which may result in strange or unethical behaviors. The research on security and privacy of big data analytics (BDA) models still devotes less attention to the impact of similar solutions that assume distributed architectures and BDA models for IoT [59]. Several researchers agree that the best trade-off between utility and disclosure risk can be found at the time of model inference when there exist real data to evaluate the data utility and the impact of its disclosure, as opposed to estimating the risk a priori [60]. BDA pipeline modules are owned and managed by multiple operators, each with its own interests and agenda; therefore, we cannot always postpone all disclosure control to the time of analytics computation. In this context, noninteractive randomization at the time of data acquisition, while decreasing utility, can provide maximum flexibility and best accommodate provisions for compliance with regulations, ethics, and cultural factors.

Considering the above, to address the security and privacy concerns, a state of the art IoT/IoMT healthcare solution must combine novel and standardized technologies to provide lightweight and usable mechanisms for the authentication of its entities (devices, applications, users, etc.) [61] and the protection of their resources through strong, unambiguous, and fine-grained authorization services. The XACML authorization engine can form the basis of this endeavor, developing dynamic authorization services and providing the necessary variables (operational or situational context, as well as privacy requirements and other scenario/use case peculiarities). Privacy-aware features can be embedded into the policy definitions. Developed solutions for back end security must allow the creation of secure and privacy-preserving communications within and from the cloud infrastructure to the smart home and healthcare service providers in an end-to-end manner. The privacy controls implemented can also include differential privacy and selective data obfuscation and randomization, both for raw data and for outcomes of the data analytics, learning, and evolution processes. The combination of the above guarantees visibility of the system's status and consequent enhanced operator control and accountability. The platform must provide a significantly higher level of security and privacy than what is currently available in the domain to unambiguously alleviate the pertinent concerns.

2.5 Smart healthcare applications—state-of-the-art research efforts

Within the landscape sketched in the previous sections and motivated by the significant benefits of IoT/IoMT-enabled smart healthcare applications, there is a plethora of efforts driven by the research and industry communities that aim to overcome the associated challenges and realize the full potential of these technologies toward improving the health, well-being, and independent living of patients and the elderly [34,62,63]. In this context, the following subsections highlight some state of the art research efforts on the topic, presenting three research projects that have recently started or will soon start tackling said issues, each proposing a novel approach and investigating different angles of the IoT/IoMT-enabled smart healthcare landscape. More specifically, the presented projects include SMART BEAR, sustAGE and xVLEPSIS.

2.5.1 SMART BEAR—smart living solution platform for the elderly

The SMART BEAR project aims to provide an intelligent and personalized digital solution for sustaining and extending healthy and independent living by implementing an affordable, accountably secure, and privacy-preserving innovative platform. This system boasts off-the-shelf smart and medical devices to support the healthy and independent living of elderly people with five prevalent health-related conditions: HL, CVDs, CIs, MH issues, and BDs, as well as frailty. This will be achieved through intelligent, evidenced-based interventions on lifestyle, medically significant risk factors, and chronic disease management. These interventions are enabled by the utilization of continuous and objective medical and environment sensing, assistive technologies, and big data analytics.

In more detail, the SMART BEAR platform integrates heterogeneous sensors and assistive devices that collect and analyze data streams from the activities of the elderly with modules that extract the necessary evidence to design personalized interventions to promote healthy and independent living. The platform will also be connected to hospital and other healthcare service systems to obtain data specific to the end users (e.g., medical history) that will need to be considered in making decisions for interventions. SMART BEAR will leverage big data analytics and learning capabilities, allowing for large scale analysis of the abovementioned collected data, to generate the evidence required for making decisions about personalized interventions. Privacy-preserving and secure by design data handling capabilities protect data at rest, in processing, and in transit and will comprehensively cover all the components and connections utilized by the SMART BEAR platform. An overview of the SMART BEAR platform is depicted in Fig. 2.1. To achieve the above, SMART BEAR will build on the platform developed within the H2020 project EVOTION (http://h2020evotion.eu/) to support evidence based public health policies formation and monitoring. The EVOTION platform supports: (1) the continuous collection of medical, physiological, and lifestyle data from heterogeneous resources including hospitals, biosensors, advanced hearing aids, and mobile phones and (2) the analysis

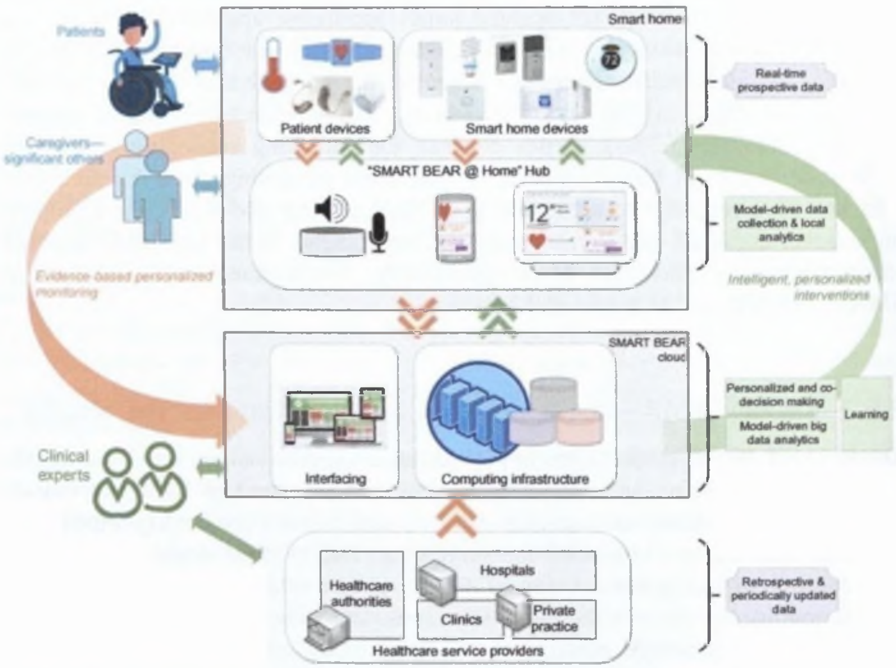

FIGURE 2.1

The SMART BEAR concept.

of these data, driven by high-level big data analytics and decision models to generate evidence useful for making public health policy level interventions [64–66]. The EVOTION platform is currently used in five hospitals in Greece and the United Kingdom, collecting real-time data from more than 1000 hearing aid users.

Key areas of innovation for SMART BEAR will include:

1. integration with IoT enablers and platforms (e.g., FI-WARE, Copernicus, consumer smart ecosystems), in order for SMART BEAR to extend the connectivity of the EVOTION platform to support new medical devices, wearables, smart home/IoT sensors and actuators, and smart environment infrastructures;
2. development of new high-level data analytics and decision models to support the intelligent and personalized interventions required for enhancing the healthy and independent living of the elderly;
3. integration of the EVOTION platform with a continuous security and privacy assurance platform to provide the continuous auditability and transparency needed for ensuring the SMART BEAR platform's trustworthiness by its end users, and
4. testing and validation of the above at a much greater scale, involving 5000 participants across five countries.

In developing the above extensions, special consideration will be given to creating an extensible and sustainable platform, open for wider adoption in the connected health ecosystem.

2.5.1.1 Targeted pilot environments

The SMART BEAR platform will be tested and validated through five large scale pilots, involving 5000 elderly users living at home in Greece, Italy, France, Spain, and Romania. The pilots will enable the evaluation of the platform in the context of healthcare service delivery by private and public providers at the regional, state, and EU levels, and demonstrate its efficacy, extensibility, sustainability, and cost effectiveness for the individual and the healthcare system. SMART BEAR will benefit from this diversity as data coming from all pilots will be collected and evaluated.

More specifically, the Greek pilot will run in two regions with different characteristics in order to evaluate the efficiency of the SMART BEAR solution in different socioeconomic conditions. These will be the Municipality of Palaio Faliro (a metropolitan area with approximately 10,000 people over 65 years of age) and the Region of Peloponnese (a rural area with a significant portion of elderly population). The Italian pilot will cover both rural and urban territories in Lombardy, so as not to restrict the sampling of this pilot to a single geographical area. Two areas are covered by the pilot: the metropolitan area of Milan (8.2 million inhabitants over an area of about 13,000 km^2) and the District of Crema (150,000 inhabitants over an area of about 573 km^2). The two areas are very different because of their extent, environmental conditions, urban services, and population. Concerning the French pilot, two regions are considered as possible and interesting experimentation areas: (1) Île-de-France (the Paris region), the area with the largest number of elderly people (and thus, of dependent elderly people); (2) Nouvelle Aquitaine (particularly the "Creuse" department), the region where the population is the oldest and where many innovative eHealth programs and projects are developed for elderly people, and (3) Bretagne, where the elderly people are the healthiest and which is an innovative and dynamic region in the eHealth field. In the Spanish pilot, the focus will be on the Basque Country, spanning an area of about 7000 km^2 with 2 million inhabitants, and one of the European regions most affected by the aging process. The pilot will cover independent elderly users living at home, seniors living in rural areas, as well as those living in collective structures, such as senior residences. Finally, in the Romanian pilot, participants will come mainly from the capital Bucharest, with a population of about 2 million people, of which 17% are over 65 (359,182). Bucharest is the area with both the largest number of elderly people (three times higher than in any other administrative region of the country) and the largest number of dependent elderly people.

2.5.1.2 The SMART BEAR consortium

SMART BEAR participants collectively constitute a consortium capable of achieving the project objectives, both well-suited and committed to the tasks assigned to them. The SMART BEAR consortium consists of 25 organizations, including four big industry partners in the ICT domain (ATOS Spain S.A. from Spain; Philips Electronics Nederland B.V. from the Netherlands; International Business Machines Corporation from Israel; and Lombardia Informatica from Italy). Moreover, the SMART BEAR consortium includes five partners from the healthcare domain (Comunita' Sociale Cremasca and the Fondazione Centro San Raffaele from Italy; CATEL from France; MUTUALIA from Spain; and Fundatia Ana Aslan International from Romania), as well as two local authorities (Region of Peloponnese and Municipality of Palaio Faliro from Greece). Part of the consortium are also eight large academic/research organizations (CNR ICAR from Italy; Foundation for Research and Technology–Hellas, National Kapodistrian University of Athens, and University of Ioannina from Greece; Università degli Studi di Milano from Italy; Universidad del País Vasco/Euskal Herriko Unibertsitatea from Spain; City, University of London from the United Kingdom, and Institute of Communication & Computer Systems from Greece) as well as six SMEs (Sphynx Technology Solutions AG from Switzerland, StreamVision from France, IT Support Solutions from Romania, Innovatec from Spain, Athens Technology Centre from Greece, and Bird and Bird from the United Kingdom). All these providers bring not only their technological expertise but also their entrepreneurial aspiration regarding their role in creative industries.

2.5.2 sustAGE—smart environments for person-centered sustainable work and well-being

sustAGE[9] is a person-centered smart solution that aims to promote the concept of "sustainable work" for EU industries, thus supporting the well-being, wellness at work, and productivity of aging employees through three main dimensions. The first dimension is directed toward improving occupational safety and health via risk assessment and prevention strategies based on workplace and person-centered health surveillance monitoring. The second dimension aims to promote the well-being of employees via personalized recommendations for physical and MH improvement. The third dimension supports decision-making related to task/job role modifications and aims to optimize overall workforce productivity by assessing the abilities of individual persons (e.g., physical, mental, social) in relation to work demands and risks. The sustAGE solution explores two industry domains with significant challenges and requirements, specifically (1) manufacturing and (2) transportation and logistics.

2.5.2.1 The industry domains

2.5.2.1.1 The case of assembly line workers in the automotive industry

There are hundreds of tasks in the manufacturing assembly process, which differ in terms of posture, workload, and complexity and require both manual labor as well as significant cognitive workload. In the automotive industry, assembly lines can produce two to three different models of a vehicle, each with dozens of possible variations. There is a small tolerance for errors in an often customizable production unit; therefore, workers need to be constantly aware of the specific order and customizations needed to be made. Furthermore, to choose the best match between task and worker in both repetitive short-cycle task operations and complex tasks, worker profiling on an individual and frequent basis is necessary to assess a worker's physical abilities and mental skills. To further take into account age-related changes, it is important to monitor both the environmental conditions and the worker's health state and actions to derive information on the individual's workload that may further impact their physical and mental state. Actions to be monitored are user proximity to critical areas, repetitive movements, bend or twisted postures, or pushing/pulling/lifting an object, along with the temporal aspects of the action (e.g., time to complete the action, pace).

2.5.2.1.2 The case of port workers in the transportation and logistics industry

Port work activities involve loading and unloading procedures and transport and storage of goods (e.g., container movement and roll on/roll off). Pilotage, workboat and tug operation, ship repairs, vessel traffic management, and similar marine activities are also involved. Dock workers are usually exposed to stressful

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[9] http://www.sustage.eu (accessed on June 8, 2019).

and dangerous working conditions. Commonly shift work (morning, afternoon, night) can result in sleep deprivation, misalignment of circadian rhythms, drowsiness, and performance deficits. Noise, vibrations, dust, wind, and tide commonly occur in ports. Workers who perform handwork and require physical strength to carry out activities are prone to musculoskeletal disorders. Beyond the physical extent of port work, the mental demands of attention and concentration at work are important as workers need to be continuously alert. The main case of interest in sustAGE regards the loading/unloading procedures of containers, in which the system monitors the container crane operator and the workers involved in the loading/unloading procedures as well as other moving objects/humans in proximity to the crane during maneuvering. The actions to be detected in this case to support the analysis, profiling, and recommendations of the system are fatigue, as derived by tracked movements along with temporal properties, as well as physiological measurements and proximity of workers to critical areas and moving objects.

2.5.2.2 Internet of Things ecosystem and system functionalities

The developed system functionalities build upon an IoT ecosystem based on off-the-shelf sensors integrated in daily devices and in the work environment, considering both indoor (manufacturing) and outdoor (port) working conditions. The system gathers contextual information from the working environment and from users' physiological signals, tasks, activities, and behavioral patterns, in order to support user profiling and provide personalized recommendations for better managing health, wellness and safety. The sustAGE technology will consider information-rich micromoments[10] (a highly investigated topic of leading technology companies like Google, Microsoft, and Facebook, geared to be the "next big thing" in intelligent system design) to process the short- and long-term aspects of symbiotic interaction, to identify patterns of human behavior, draw correlations between actions, predict what humans do and do not want, improve user's acceptance, and engage users in a successful long-term interaction. Therefore, the notion of time, the consideration of real-world phenomena, and interactions in association with the course of time is very important. Measurements collected from different devices and modules of the system support the definition of key micromoments for future user profile updates, recommendations, and notifications. Different micromoments related to the user daily schedule, work environment, workload, physical/emotional/mental state, and social activities are used (Table 2.2).

Indicative key features of the sustAGE solution are:

- *Monitoring of user actions and behaviors in work environment and personal life.* An IoT ecosystem is exploited, comprised of smart sensors and mobile devices for locating and tracking users in real time and for the fine-grained

[10] https://www.thinkwithgoogle.com/marketing-resources/micro-moments/

Table 2.2 List of indicative micromoments.

Category	Indicative list of micromoments
Work environment	High/low temperature, noise level, pollution, wet/dry weather
Work/task	Work shift, task onset, task completion, task type (repetitive work, bent or twisted body posture), push/pull an object, lifting heavy load, task switch, pace, task break, injury from accident/body part
Daily schedule	Arriving at-leaving from work, lunch/dinner, medication intake, wake-up, go to sleep, meet friends
Physical	Health check, instance of pain, high/low pulse rate, body temperature, walking, resting, steps count during activity, fatigue
Mental	Stress/frustration, depression sign, emotional state changes, state communication/verification by the system
HR	Sick days, tasks increasing/decreasing productivity, employee requests for task changes

detection of user actions and states. By combining information from multiple sources, the system will be able to support user profiling in a privacy-preserving manner and provide context-aware recommendations and analytics.

- *Abstraction and episodic knowledge.* Analyze users' activities and memorize important episodes aiming to keep important information related to past human activities and states. Building on users' micromoments, the system will memorize actions that users need to take and will better predict user reactions by considering their activity in similar past situations.
- *Multiaspect user profiling.* The aggregation of past user-specific knowledge, comprised of user preferences, the results of user performance in work- and training-related activities, and long-term abstractions will allow a more complete physical, mental, and psychosocial user profiling. The collection and analysis of related information will be done transparently, without user intervention.
- *Multilevel personalized recommendations.* Recommendations with respect to three different levels are provided, namely physical, mental, and workforce. Recommendations on the first two will be managed by the individual person measuring the impact on the work ability, health, and well-being, whereas the workforce recommendations will be managed by the management. The system will consider spatiotemporal aspects, taking into account the user's activity, state, time and location, the daily and weekly schedule and will recommend an activity at the right moment.
- *Safe working environment.* Continuously monitor both the environmental conditions in the working area (i.e., manufacturing floor or port dock) and workers' health-related signs in order to detect critical cases and workload issues early and to provide alerts to specific workers, who must take short breaks or switch tasks for the rest of their shift or over longer intervals.

The IoT infrastructure comprises of the following devices/sensors:

- *Environmental sensors* measuring air temperature, humidity, air quality, pressure, dust concentration and noise based on Raspberry Pi/Arduino custom sensors that are open source, low cost, accurate, and durable.
- *Cameras* installed in key working areas. For the manufacturing indoor environment of the assembly line, passive stereo cameras are used to monitor postures and repetitive actions of users, whereas for the port outdoor environment, monocular cameras with varying focal lengths are used to monitor crane operators and workers involved in loading/unloading of containers and people/objects in the vicinity of the crane.
- For localization in indoor environments, *beacons* achieve a precision of up to 10–20 cm within a range of up to 100 m, whereas for outdoor environments the *GNSS receivers* built-in smartphones are used.
- *Wristwatch devices* gather physiological measurements and are able to trigger notifications to users from the system. The selected device should offer software development kits (SDKs) and APIs to facilitate its programmability and access to the data.
- *Smartphone* devices able to support Galileo, offering centimeter accuracy and the ability to communicate with the wristwatch device.

The above set of devices/sensors can collaboratively provide information on different user activities/actions (e.g., walk, bend, stand/sit, push/pull object), state (e.g., fatigue, discomfort), temporal aspects, and specific events in the environment (e.g., user monitoring in specific areas, proximity to hazardous conditions). Moreover, the smartphone is the primary device for communication and multimodal interaction supporting natural language understanding and sentiment analysis. The adopted IoT configuration exhibits the advantages of unobtrusive user-context interaction monitoring in a privacy-preserving way considering that in private life, outside the working environment, only the wristwatch and the mobile device are to be used. The system supports raw data processing near the end-devices to prevent potentially privacy-sensitive information from being sent to the upper layers of the platform in the cloud.

2.5.2.3 The sustAGE consortium

The sustAGE consortium comprises a unique blend of partners from disciplines that span a broad spectrum. The project brings together one of the largest European automotive industries (Centro Ricerche Fiat Scpa, Italy), one of Greece's most important maritime ports (Heraklion Port Authority, Greece), a global leader in ICT products and services (Software AG, Germany), SMEs providing expertise in interactive technologies for e-health (Imaginary Srl., Italy) and distributed systems (AEGIS IT Research UG, Germany), three top European universities in the areas of embedded intelligence for health care and well-being (University of Augsburg, Germany), aging and neurodegenerative diseases (Universidad Nacional de Educación a Distancia, Spain), positioning and sensors (Aristotle University of

Thessaloniki, Greece), two top European research centers in the areas of ergonomics, working environments and human factors (Forschungsgesellschaft für Arbeitsphysiologie und Arbeitsschutz E.V.), and emerging ICT research (Foundation for Research and Technology—Hellas).

2.5.3 xVLEPSIS—an intelligent noninvasive biosignal recording system for infants

Over the last years there is a strong interest in improving patient monitoring in an attempt to facilitate clinicians providing error free decisions while saving time and improving the overall quality of patient care. Such approaches are particularly useful in time critical settings, such as the intensive care unit of the hospital. A stronger effort is required to provide high quality, multimodal, real-time neonate monitoring platforms that can be ubiquitous and unobstructive while at home.

xVLEPSIS[11] is an advanced system for the prediction of potentially hazardous events related to infants. As many pathological situations can occur during an infant's night sleep that can potentially be threatening to health if not detected promptly, there is an imperative for early detection of medical emergencies during infant sleep through an unobtrusive and noninvasive detection system. Invasive devices and sensors could disrupt the infant's sleeping phases that are extremely important for their development and degrade the quality of their rest.

xVLEPSIS uses a scalable system comprising a "smart" bed mattress and a camera positioned to monitor the infant cradle. Without disturbing the infant's sleep, the system can detect possible pathological conditions.

2.5.3.1 Integration of smart biosignal sensors in a detection system for hazardous conditions

The xVLEPSIS system will incorporate diverse user-friendly electronic smart sensors, integrated under a "smart" mattress, in combination with a high-resolution baby monitor. In brief, the following biosignals will be recorded, analyzed, and investigated for their applicability as biomarkers for certain pathologies:

- video recording using a high-resolution camera and audio recording using a high definition microphone;
- ballistocardiogram [67] recording, which records sudden blood ejections into the great vessels with each heartbeat;
- pressure sensors under the bed mat record and plot repetitive body movements during sleep; and
- temperature and humidity detection using suitable sensors under the bed mat.

[11] https://xvlepsis.gr/en (accessed on June 8, 2019).

The development of an intelligent system that will detect potentially hazardous pathological conditions with the use of sophisticated machine learning techniques will lead to:

1. A mobile or smart watch–based notification system, which will alert the parents in the case of emergency.
2. Continuous biosignal recording, throughout the infant's sleep. The recorded data could be sent to the doctor or the hospital, in the case that an abnormality is detected, or they could be evaluated by the doctor during regular infant examination, in the case nothing critical is detected. Therefore, the pediatrician will be able to examine and evaluate all the available medical data and detect any incidents that may have occurred at night without having been perceived by the parents.

Many advantages arise from the development of a low-cost product with all the aforementioned features:

- Continuous recording of high definition video and audio will allow for a more effective monitoring of the infant, whereas the pathological situations detection system will lead to the discovery of incidents that would otherwise remain unnoticed.
- The proposed noninvasive monitoring system will aid the diagnosis and proper treatment of medical disorders that can occur while the parents are not present (e.g., febrile convulsions, epileptic seizures, or apnea).
- Pediatricians always face the challenge of evaluating medical incidents solely based on the information that parents provide, which is not objective and accurate, especially during the first year of infants life. The proposed integrated system offers the medical professionals in charge the opportunity to assess those incidents based on detailed recorded biosignals and, thus, form a better opinion on the diagnosis.
- The use of innovative machine learning algorithms performed on the multimodal medical signals will significantly aid the detection of new quantitative biomarkers of the relevant diseases.
- The medical database that will be implemented will significantly contribute to the research and study of early childhood disorders.

Such a system is expected to effectively notify the parents and enable doctors to identify specific pathologies. The system will continuously and unobtrusively record important biosignals and analyze them using sophisticated machine learning algorithms, suitable for pathology-specific pattern identification and biomarker extraction. The software to be developed will act as a recommendation and alarming system to notify the parents and/or the physician, if needed, by means of a notification center hosted in a smartphone and/or a smartwatch. A dedicated repository will host raw signals for future reference or doctor's referral.

2.6 Conclusion

The role of smart biosensors and IoT is significant in modern medical care. Patients, care-providers and health professionals can strongly benefit from smart applications developed on top of such infrastructures. In this chapter, we presented the challenges and opportunities from the application of smart biosensors in healthcare and described three state of the art solutions that employ smart sensors in this context. The applications demonstrate how smart living solutions can be developed on top of an ecosystem that combines IoT and smart biosensors to record and analyze biosignals in a noninvasive way and allow the early detection and prevention of potentially hazardous pathological conditions. Since there are still many challenges concerning data privacy, data aggregation and integration, and intelligent decision-making to be overcome, this effort has to be intensified. Future efforts should focus on the use of data analysis and data mining techniques as well as the development of machine learning models that can efficiently handle biosignal data streams and effectively decide on the proper actions to take.

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References

[1] S. Ajami, F. Teimouri, Features and application of wearable biosensors in medical care, J. Res. Med. Sci. 20 (12) (2015) 1208–1215. Available from: https://doi.org/10.4103/1735-1995.172991.

[2] P. Mehrotra, Biosensors and their applications – a review, J. Oral Biol. Craniofacial Res. 6 (2) (2016) 153–159. Available from: https://doi.org/10.1016/j.jobcr.2015.12.002.

[3] WHO. World Report on Ageing and Health, World Health Organization. Available from: <https://apps.who.int/iris/bitstream/handle/10665/186463/9789240694811_eng.pdf?sequence=1>, 2015 (accessed 08.06.19).

[4] T. Vos, A.A. Abajobir, K.H. Abate, C. Abbafati, K.M. Abbas, F. Abd-Allah, et al., Global, regional, and national incidence, prevalence, and years lived with disability for 328 diseases and injuries for 195 countries, 1990–2016: a systematic analysis for the Global Burden of Disease Study 2016, Lancet 390 (10100) (2017) 1211–1259.

[5] WHO. Cardiovascular Diseases (CVDs) Key Facts, World Health Organization. Available from: <http://www.who.int/en/news-room/fact-sheets/detail/cardiovascular-diseases-(cvds)>, 2017 (accessed 08.06.19).

[6] L. Leto, M. Feola, Cognitive impairment in heart failure patients, J. Geriatr. Cardiol. JGC 11 (4) (2014) 316.

[7] EIPAHA—European Innovation Partnership on Active and Healthy Ageing. A compilation of good practices on prevention and early diagnosis of frailty and functional decline, both physical and cognitive in older people, European Union, Brussels, Belgium. Available from: <https://ec.europa.eu/research/innovation-union/pdf/active-healthy-ageing/gp_a3.pdf>, 2012 (accessed 08.06.19).

[8] K. Murad, D.W. Kitzman, Frailty and multiple comorbidities in the elderly patient with heart failure: implications for management, Heart Fail. Rev. 17 (4–5) (2012) 581–588.

[9] K. Jekel, M. Damian, C. Wattmo, L. Hausner, R. Bullock, P.J. Connelly, et al., Mild cognitive impairment and deficits in instrumental activities of daily living: a systematic review, Alzheimer's Res. Therapy 7 (1) (2015) 17.

[10] J. Chowhan, M. Denton, C. Brookman, S. Davies, F.K. Sayin, I. Zeytinoglu, Work intensification and health outcomes of health sector workers, Personnel Rev. 48 (2) (2019) 342–359.

[11] C. Bhatt, N. Dey, A.S. Ashour (Eds.), Internet of Things and Big Data Technologies for Next Generation Healthcare, Springer, 2017. 978-3-319-49736-5.

[12] M.A. Razzaque, M. Milojevic-Jevric, A. Palade, S. Clarke, Middleware for Internet of Things: a survey, IEEE Int. Things J. 3 (1) (2016) 70–95. Available from: https://doi.org/10.1109/JIOT.2015.2498900.

[13] A.B. Brush, B. Lee, R. Mahajan, S. Agarwal, S. Saroiu, C. Dixon, Home automation in the wild, in: Proceedings of the 2011 Annual Conference on Human Factors in Computing Systems—CHI '11, ACM Press, New York, 2011, p. 2115. ISBN 9781450302289. doi: 10.1145/1978942.1979249.

[14] Y.F. Gomes, D.F.S. Santos, H.O. Almeida, A. Perkusich, Integrating MQTT and ISO/IEEE 11073 for health information sharing in the Internet of Things, in: 2015 IEEE International Conference on Consumer Electronics (ICCE), 2015, pp. 200–201. ISBN 978-1-4799-7543-3. doi: 10.1109/ICCE.2015.7066380.

[15] S.-M. Kim, H.-S. Choi, W.-S. Rhee, IoT home gateway for auto-configuration and management of MQTT devices, in: 2015 IEEE Conference on Wireless Sensors (ICWiSe), 2015, pp. 12–17. ISBN 978-1-4673-9398-0. doi: 10.1109/ICWISE.2015.7380346.

[16] D. Driscoll, A. Mensch, T. Nixon, A. Regnier, Devices profile for web services, version 1.1, 2009. Available from: <http://docs.oasis-open.org/ws-dd/dpws/wsdd-dpws-1.1-spec.pdf> (accessed 08.06.19).

[17] K. Fysarakis, I. Papaefstathiou, C. Manifavas, K. Rantos, O. Sultatos, Policy-based access control for DPWS-enabled ubiquitous devices, in: Proceedings of the 2014 IEEE Emerging Technology and Factory Automation (ETFA), Barcelona, Spain, 2014, pp. 1–8. IEEE. ISBN 978-1-4799-4845-1. doi: 10.1109/ETFA.2014.7005233.

[18] Z. Shelby, K. Hartke, C. Bormann, The constrained application protocol (CoAP). Available from: <https://tools.ietf.org/html/rfc7252>, 2014.

[19] G. Elhayatmy, N. Dey, A.S. Ashour, Internet of Things based wireless body area network in healthcare, Internet of Things and Big Data Analytics Toward Next-Generation Intelligence., Springer, Cham, 2018, pp. 3–20.

[20] A. Jain, B. Vishal, Concoction of ambient intelligence and big data for better patient ministration services, Int. J. Ambient Comput. Intell. 8 (4) (2017) 19–30.

[21] M.A.A. Da Cruz, J.J.P.C. Rodrigues, J. Al-Muhtadi, V.V. Korotaev, V.H.C. de Albuquerque, A reference model for Internet of Things middleware, IEEE Int.

Things J. 5 (2) (2018) 71–883. Available from: https://doi.org/10.1109/JIOT.2018.2796561.

[22] I.C. Jeong, D. Bychkov, P.C. Searson, Wearable devices for precision medicine and health state monitoring, IEEE Trans. Biomed. Eng. 66 (5) (2019) 1242–1258. Available from: https://doi.org/10.1109/TBME.2018.2871638.

[23] D. Dias, J. Paulo Silva Cunha, Wearable health devices-vital sign monitoring, systems and technologies, Sensors 18 (8) (2018) 2414. Available from: https://doi.org/10.3390/s18082414.

[24] Y. Mendelson, D.K. Dao, K.H. Chon, Multi-channel pulse oximetry for wearable physiological monitoring, in: Proceedings of the 2013 IEEE International Conference on Body Sensor Networks (BSN), May 6–9, 2013, MA, 2013, pp. 1–6.

[25] T. Xiao-Fei, Z. Yuan-Ting, C.C.Y. Poon, P. Bonato, Wearable medical systems for p-Health, IEEE Rev. Biomed. Eng. 1 (2008) 62–74. Available from: https://doi.org/10.1109/RBME.2008.2008248.

[26] A. Henriksen, M. Haugen Mikalsen, A.Z. Woldaregay, et al., Using fitness trackers and smartwatches to measure physical activity in research: analysis of consumer wrist-worn wearables, J. Med. Internet. Res. 20 (3) (2018) e110. Available from: https://doi.org/10.2196/jmir.9157.

[27] R. Zangróniz, A. Martínez-Rodrigo, J.M. Pastor, M.T. López, A. Fernández-Caballero, Electrodermal activity sensor for classification of calm/distress condition, Sensors 17 (10) (2017) 2324. Available from: https://doi.org/10.3390/s17102324.

[28] W.Z. Khan, Y. Xiang, M.Y. Aalsalem, Q. Arshad, Mobile phone sensing systems: a survey, IEEE Commun. Surv. Tutor. 15 (1) (2013) 402–427.

[29] Y. Ranjan, M. Kerz, Z. Rashid, S. Böttcher, R.J. Dobson, A.A. Folarin, Radar-base: a novel open source m-health platform, in: Proceedings of the ACM Intel. Joint Conference and 2018 International Symposium on Pervasive and Ubiquitous Computing and Wearable Computers, UbiComp '18, 2018, pp. 223–226.

[30] J. Frankle, M. Carbin, The lottery ticket hypothesis: finding sparse, trainable neural networks. Available from: <https://arxiv.org/abs/1803.03635>, 2018.

[31] A. Kumar, H. Kim, G.P. Hancke, Environmental monitoring systems: a review, IEEE Sensor. J. 13 (4) (2013) 1329–1339. Available from: https://doi.org/10.1109/JSEN.2012.2233469.

[32] G. Mois, S. Folea, T. Sanislav, Analysis of three IoT-based wireless sensors for environmental monitoring, IEEE Trans. Instrum. Meas. 66 (8) (2017) 2056–2064.

[33] E. Kim, S. Helal, D. Cook, Human activity recognition and pattern discovery, IEEE Pervasive Comput. 9 (1) (2010) 48–53.

[34] A.A. Chaaraoui, P. Climent-Pérez, F. Flórez-Revuelta, A review on vision techniques applied to human behaviour analysis for ambient-assisted living, Expert Syst. Appl. 39 (12) (2012) 10873–10888. Available from: https://doi.org/10.1016/j.eswa.2012.03.005.

[35] R. Poppe, A survey on vision-based human action recognition, Image Vision Comput. 28 (6) (2010) 976–990. Available from: https://doi.org/10.1016/j.imavis.2009.11.014.

[36] J. Shotton, T. Sharp, A. Kipman, A. Fitzgibbon, M. Finocchio, A. Blake, et al., Real-time human pose recognition in parts from single depth images, Commun. ACM 56 (1) (2013) 116–124. Available from: https://doi.org/10.1145/2398356.2398381.

[37] M. Sigalas, M. Pateraki, P. Trahanias, Full-body pose tracking – the top view reprojection approach, IEEE Trans. Pattern Anal. Mach. Intell. 38 (8) (2016) 1568–1582.

[38] C. Feichtenhofer, A. Pinz, A. Zisserman, Convolutional two-stream network fusion for video action recognition, in: IEEE Conference on Computer Vision and Pattern Recognition (CVPR), 2016, pp. 1933-1941.
[39] F. Moerchen, Algorithms for time series knowledge mining, Proceedings of the 12th ACM SIGKDD international conference on Knowledge discovery and data mining, ACM, 2006, pp. 668–673.
[40] M. Stacey, C. McGregor, Temporal abstraction in intelligent clinical data analysis: a survey, Artif. Intell. Med. 39 (1) (2007) 1–24.
[41] M. Madkour, D. Benhaddou, C. Tao, Temporal data representation, normalization, extraction, and reasoning: a review from clinical domain, Comput. Meth. Programs Biomed. 128 (2016) 52–68.
[42] W. Raghupathi, V. Raghupathi, Big data analytics in healthcare: promise and potential, Health Inform. Sci. Syst. 2 (2014) 3.
[43] E. Vayena, J. Dzenowagis, J.S. Brownstein, A. Sheikh, Policy implications of big data in the health sector, Bull. World Health Organ. 96 (1) (2018) 66–68.
[44] S. Ilarri, R. Hermoso, R. Trillo-Lado, M.D.C. Rodríguez-Hernández, A review of the role of sensors in mobile context-aware recommendation systems, Int. J. Distrib. Sens. Netw. 11 (11) (2015) 489264.
[45] F. Casino, C. Patsakis, E. Batista, F. Borràs, A. Martínez-Ballesté, Healthy routes in the smart city: a context-aware mobile recommender, IEEE Softw. 34 (6) (2017) 42–47.
[46] Y. Lin, J. Jessurun, B. De Vries, H. Timmermans, Motivate: towards context-aware recommendation mobile system for healthy living, in: 2011 5th IEEE International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) and Workshops, 2011, pp. 250–253.
[47] S. Gupta, S.P. Sood, D.K. Jain, 'Let's exercise': a context aware mobile agent for motivating physical activity, Emerging Research in Computing, Information, Communication and Applications, Springer, New Delhi, 2016, pp. 511–520.
[48] V. Ponce, J.P. Deschamps, L.P. Giroux, F. Salehi, B. Abdulrazak, QueFaire: context-aware in-person social activity recommendation system for active aging, in: International Conference on Smart Homes and Health Telematics, Springer, Cham, 2015, pp. 64–75.
[49] J. Bauer, R.C. Staudemeyer, H.C. Pöhls, A. Fragkiadakis, ECDSA on things: IoT integrity protection in practice, Proceedings of the Information and Communications Security (ICICS 2016), Springer, 2016.
[50] T. Marktscheffel, W. Gottschlich, W. Popp, P. Werli, S.D. Fink, A. Bilzhause, et al., QR code based mutual authentication protocol for Internet of things, in: Proceedings of the IEEE 5th workshop on IoT-SoS: Internet of Things Smart Objects and Services (WOWMOM SOS-IOT 2016), 2016.
[51] R. Hummen, J.H. Ziegeldorf, H. Shafagh, S. Raza, K. Wehrle, Towards viable certificate-based authentication for the Internet of things, in: Proceedings of the 2nd ACM Workshop on Hot Topics on Wireless Network Security and Privacy, ACM, April 2013, pp. 37–42.
[52] M. Bentounsi, S. Benbernou, M.J. Atallah, Privacy-preserving business process outsourcing, in: Proceedings of the IEEE 19th International Conference on Web Services, 2012, pp. 662–663.
[53] C. Gentry, Fully homomorphic encryption using ideal lattices, in: Proceedings of the Forty-First Annual ACM Symposium on Theory of Computing, 2009, pp. 169–178.

[54] M. Li, S. Yu, K. Ren, W. Lou, Y.T. Hou, Toward privacy-assured and searchable cloud data storage services, IEEE Netw. 27((4)) (2013) 56–62.
[55] M. Van Dijk, A. Juels, On the impossibility of cryptography alone for privacy-preserving cloud computing, in: Proceedings of the 5th USENIX Conference on Hot Topics in Security, 2010, pp. 1–8.
[56] B. Parducci, H. Lockhart, E. Rissanen, eXtensible Access Control Markup Language (XACML) Version 3.0, 2013.
[57] A.X. Liu, F. Chen, J. Hwang, T. Xie, Designing fast and scalable XACML policy evaluation engines, IEEE Trans. Comput. 60 (12) (2011) 1802–1817. Available from: https://doi.org/10.1109/TC.2010.274. 2011. ISSN 00189340.
[58] E. Rissanen, "XACML v3.0 Privacy Policy Profile Version 1.0," OASIS. [Online]. Available from: <http://docs.oasis-open.org/xacml/3.0/privacy/v1.0/xacml-3.0-privacy-v1.0.html>, 2015 (accessed 08.06.19).
[59] E. Damiani, G. Gianini, M. Ceci, D. Malerba, Toward IoT-friendly learning models, in: IEEE 38th International Conference on Distributed Computing Systems (ICDCS), 2018, pp. 1284–1289.
[60] Q. Jia, L. Guo, Z. Jin, Y. Fang, Preserving model privacy for machine learning in distributed systems, IEEE Trans. Parallel Distrib. Syst. 29 (8) (2018) 1808–1822. Available from: https://doi.org/10.1109/TPDS.2018.2809624.
[61] M. Yamin, A.A.S. Adnan, Improving privacy and security of user data in location based services, Int. J. Ambient Comput. Intell. (2018) 19–42. 9.1.
[62] M. Haghi, K. Thurow, R. Stoll, Wearable devices in medical internet of things: scientific research and commercially available devices, Healthc. Inform. Res. 23 (1) (2017) 4–15. Available from: https://doi.org/10.4258/hir.2017.23.1.4.
[63] N. Zhu, et al., Bridging e-Health and the Internet of Things: The SPHERE project, IEEE Intell. Syst. 30 (4) (2015) 39–46. Available from: https://doi.org/10.1109/MIS.2015.57.
[64] M. Anisetti, C. Ardagna, V. Bellandi, M. Cremonini, F. Frati, E. Damiani, Privacy-aware big data analytics as a service for public health policies in smart cities, Sustain. Cities Soc. 39 (2018) 68–77.
[65] B. Ye, I. Basdekis, M. Smyrlis, G. Spanoudakis, K. Koloutsou, A big data repository and architecture for managing hearing loss related data, in: 2018 IEEE EMBS International Conference on Biomedical & Health Informatics (BHI), IEEE, March 2018, pp. 174–177.
[66] M. Prasinos, G. Spanoudakis, D. Koutsouris, Towards a model-driven platform for evidence based public health policy making, in: Proceedings of the 29th International Conference on Software Engineering and Knowledge Engineering, 2017.
[67] L. Giovangrandi, O.T. Inan, R.M. Wiard, M. Etemadi, G.T.A. Kovacs, Ballistocardiography – a method worth revisiting, Proc. IEEE Eng. Med. Biol. Soc. (2011) 4279–4282.

Further reading

E.A. Carroll, M. Czerwinski, A. Roseway, A. Kapoor, P. Johns, K. Rowan, et al., Food and mood: just-in-time support for emotional eating, in: 2013 IEEE Humaine Association Conference on Affective Computing and Intelligent Interaction, 2013, pp. 252–257.
ENISA, Security and Resilience in eHealth Infrastructures and Services, 2015.
S. Tamane, K.S. Vijender, D. Nilanjan (Eds.), Privacy and Security Policies in Big Data, IGI Global, 2017.