# Advanced Internet of Things for Personalised Healthcare System: A Survey

Jun Qi, Po Yang, Geyong Min, Oliver Amft, Feng Dong, Lida Xu

*Abstract*—**As a new revolution of the Internet, Internet of Things (IoT) is rapidly gaining ground as a new research topic in many academic and industrial disciplines, especially in healthcare. Remarkably, due to the rapid proliferation of wearable devices and smartphone, the Internet of Things enabled technology is evolving healthcare from conventional hub based system to more personalised healthcare system (PHS). However, empowering the utility of advanced IoT technology in PHS is still significantly challenging in the area considering many issues, like shortage of cost-effective and accurate smart medical sensors, unstandardized IoT system architectures, heterogeneity of connected wearable devices, multi-dimensionality of data generated and high demand for interoperability. In an effect to understand advance of IoT technologies in PHS, this paper will give a systematic review on advanced IoT enabled PHS. It will review the current research of IoT enabled PHS, and key enabling technologies, major IoT enabled applications and successful case studies in healthcare, and finally point out future research trends and challenges.**

*Index Terms*— **Internet of Things, Personalised Healthcare, Lifelogging.**

## I. Introduction

Recently, Internet of Things (IoT) is emerging as a new paradigm in information technology aimed at building up a dynamic global network infrastructure by connecting a variety of physical and virtual 'things' with the growing mobile and sensors. IoT was initially proposed to refer to uniquely identifiable objects (things) and their virtual representations in an internet-like structure, by mean of using radio-frequency identification (RFID) technology. Later on, the concept of IoT has been extended to cover more type of 'things' with a variety of sensors, such as actuators, global positioning system (GPS) devices and mobile devices. The seamless integration and effective harness of these sensors in a platform associated to the Internet have raised up a lot of research issues, from system architecture, data processing to applications. Nowadays, IoT technology has been rapidly gaining ground as a priority multidisciplinary research topic in many academic and industrial disciplines, especially in healthcare.

Traditionally, the motivation of utilizing modern Information and communication technologies (ICT) in healthcare system is to offer promising solutions for efficiently delivering all kinds of medical healthcare services to patients, named as E-health, such as electronic record systems, telemedicine systems, personalised devices for diagnosis, etc. But, driven by a sustained increase in longevity, many developed countries in are now facing the fact that their fast-growing demographics is the over-80s. This trend brings with some key concerns about the economic viability of traditional healthcare systems, and thus it needs to design and develop more coherent and ubiquitous ICT enabled solutions for delivering high quality patient-centred healthcare services. Fortunately, due to the rapid proliferation of wearable devices and smartphone, IoT enabled technology is evolving healthcare from conventional hub based system to more personalised healthcare system. Successful utilization of IoT enabled technology in PHS will enable faster and safer preventive care, lower overall cost, improved patient-centered practice and enhanced sustainability[1]. Future IoT enabled PHS will be realized by providing highly customized access to rich medical information and efficient clinical decision making to each individual with unobtrusive and successive sensing and monitoring.

But empowering the utility of IoT enabled technology in PHS is still significantly challenging in the area considering shortage of cost-effective and accurate smart medical sensors, unstandardized IoT system architectures, heterogeneity of connected wearable devices, multi-dimensionality and high volume of data generated, and high demand for interoperability. From user-centered perspective, the successful use of IoT in PHS will also need an interoperable IoT environment for care delivery and research, tightly-coupled health data mining applications, adequate data and knowledge standards of self-empowerment and sound clinical decision-making foundation. These above challenges and needs grant a lot of opportunities to explore and investigate new concepts, algorithms and applications in IoT enabled PHS field.

In an effect to understand advance of IoT technologies in PHS, this paper conducts a survey on recent advanced IoT enabled PHS. We undertook an extensive literature review by examining relevant articles from major academic databases (IEEE Xplore, ACM digital library and Science-Direct). Key search terms include the key words 'Internet of Things', 'Healthcare', 'Pervasive Healthcare' and 'Mobile Healthcare' and a wide range of other technologies. We also reviewed the research projects related to IoT, e-health, smart healthcare, etc. The initial review shows that some recent survey papers [2] [201] have reported and analyzed some IoT related techniques for healthcare applications, like wearable sensing technologies for healthcare [2], mobile phone sensing technologies [201], or ambient intelligence for healthcare [202]. But these surveys most concentrate on examining individual layer of IoT enabled systems like sensing or data analysis, and lack of a systematic perspective review from the entire IoT eco-systems. So many

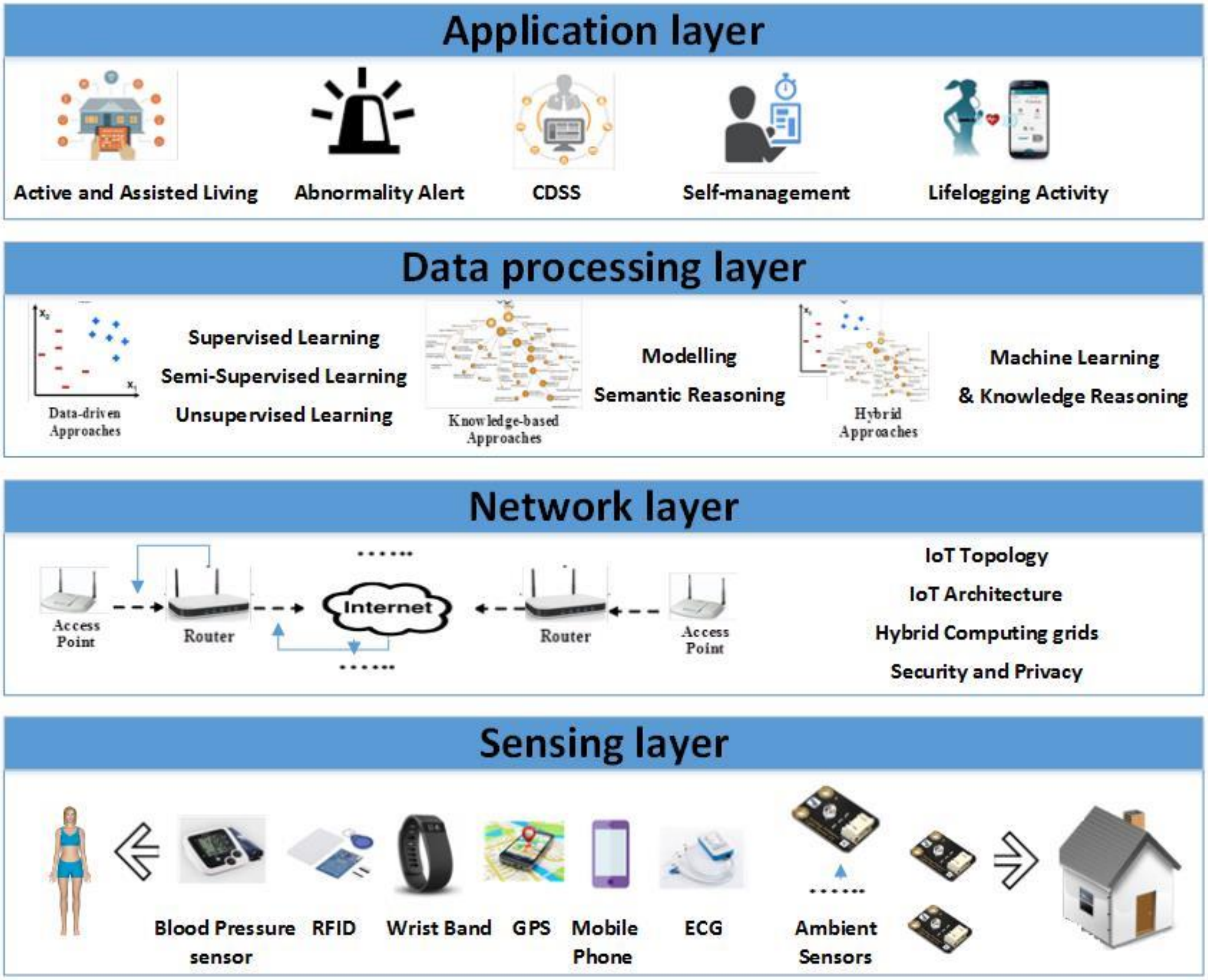


Fig.1. Four-Layers SoA in IoT enabled PHS.

research issues and factors related to the system level are ignored, for instance, the involvement of human factors in IoT systems, the security and privacy concerns of IoT architecture. Also, they rarely notice that IoT enabled healthcare is gradually transferring traditional clinic-centred health systems into more personalised and mobile-centred healthcare systems (PHS).

Therefore, the key novelty of our review will focus on a first attempt on systematically categorize PHS technologies from an classic 4-layer IoT system perspective, focusing on identifying the breadth and diversity of existing research in IoT enabled PHS, including key enabling technologies, related applications, and successful case studies in IoT enabled PHS. It explores some new potential research issues, and highlights the future research trends and challenges for researchers regarding the use of IoT in PHS.

The rest of the paper is organized as follows. Section II presents the background and current research of IoT enabled PHS. Section III reviews key enabling technologies of developing IoT enabled PHS. Section IV describes key applications and case studies related to IoT enabled PHS. Section VI discusses research challenges and future trends. Conclusion is given in Section VII.

## II. Current Research for IoT enabled PHS

The initial vision of IoT was to extend the term “Internet” into the real world embracing everyday physical objects by means of Radio Frequency Identification (RFID) technology [2-3]. Soon, as rapid advances in sensing technologies, more heterogeneous sensors – such as accelerometers, gyroscopes, altimeters and other portable low-cost devices are capable of being connected in an IoT environment. Driven by the exponential growth of commercial wearable devices and mobile apps, the concept of IoT based PHS [5] is established and become increasingly popular. These healthcare systems [25-28] use a set of interconnected devices to create an IoT network for performing healthcare activities, such as diagnosis, monitoring and remote surgeries. In terms of a well-known definition of four layers IoT system architecture, as shown in Fig.1. A number of typical of studies in a IoT enabled PHS will be categorized by sensing, networking, processing and application, as shown in Table.1.

**Table .1. Typical Studies in IoT enabled PHS Table (ACC-accelerometer; EEG-electroencephalogram; ECG-electrocardiogram; gyro-gyroscope; DT-decision tree; SVM-support vector machine; HMM-hidden Markov model)**

| *Sensing layer* | | *Network layer* | *Processing layer* | | | | *Application* | *Assessment* | |
|---|---|---|---|---|---|---|---|---|---|
| **Device specification** | **Placed position** | **Network** | **Methods** | **Users** | **Subjects** | **Accuracy** | | **Advantages** | **Limitations** |
| 1 ACC | Back | Chipcom CC2430 transceiver | Self-defined thresholds | Young healthy people | Walk, fast walk, ascend stairs, etc. | 91.5%-100% | Recognition and monitoring elder people at home. [10] | Low-cost simple algorithms; adaptive | Short time monitoring; uncontrolled environment |
| ACOR+ kinematic system | day: belt; night: chest | Bluetooth | DT | Patients, healthy people | Postures, walk, read, exercises | 77%-94% | COPD patients monitoring.[ 11] | Simple device and algorithm | The model only useful for COPD patients. |
| Multi-channel sensor module (EEG, respiration) | Head | Bluetooth | SVM | Twenty mentally healthy people | Awake, drowsy, etc | 98.5% ± 1.4%. | Lifelogging mental fatigue monitoring[ 12] | Real-time feedback on mobile device. | Mulitple sensors may incerease the cost and simplicity. |
| ACC and pressure sensors; | Feet | Bluetooth | SVM | Young, mid-aged healthy people | Postures, walk, step, sweep, cycle, jog | 92%-98% | Reduce Energy and memory on smart phone[13] | Energy efficient; real-time feedback | Smart shoes are non-universal; no mention of feasibility. |
| Wearable device | Wrist | Not mentioned | Multivariate analysis | 16 elder people | Sleep, wake | Not mentioned | Monitoring elderly health and sleep patterns[14] | Real-life environment ; high targetedsubjects | No obvious disadvantages |
| SHIM-MER's ECG and GSR | Wrist | Bluetooth | DT, Bayesian Network, SVM, K-Means | 20 people | Baseline, stressed | 92.4% | Continous human stress monitoring for interventions[15] | Inclusive of PA impact on the stress; long-term monitoring. | Patients are not considered and tested. |
| 1 3D ACC, 1 wearable camera | ACC on the belly; Camera hung over neck | ZigBee, Wi-Fi, Bluetooth | SVM | Not mentioned | Run, go downstairs, go upstairs, take an elevator, walk, etc. | 90%-99% | lifelogging health monitoring in context-aware enviornment [16] | The approach could recognize movement directions. | Lack of privacy; inconvenience in daily lives; limited subject categories. |
| Mobile phone | No strict position | Bluetooth, GSM, Wi-Fi | HMM, DT | 16 healthy people (8 F, 8 M, ages 20-45) | Still, walk, run, cycle, motor | 87.9%-96.2% | lifelogging healthecare monitoring, personal transporation[17] | No needs for phone's 6DOF; fine grained activity categories. | Not mentioned whether the model is useful for elderly or patients. |
| 1 gyro on shoe | Feet, knee | Not mentioned | Knowledge-based | 10 people, 6 people with impaired gait | Walk on level ground, walk up and down a steep, etc | >96% | A system of controlling the gait cycle of a neuroprosthesis for walking in real time [18] | Identify transitions in gait phase; present walking and non-walking activities | No obvious disadvantages |
| 1 3D ACC, 1 3D gyro, 1 3D magnetic sensor. | Upper and lower limb | Bluetooth | Kinematic modelling | 8 healthy male people (24–40 years old) | circular, rectangular motion, reach, elevation, etc | 95%-98% | home-based stroke rehabilitation [19] | low-cost, real-time robust in different motion circumstances | No obvious disadvantages |

The sensing layer for PHS aims to design and develop novel sensors or sensing technologies for effectively and efficiently collecting a variety of types of personalised health and medical information in an IoT environment. Existing sensors and wearable devices, such as inertial sensors [19], GPS (Global Positioning System) [24] , ECG [26] , EEG [29] are capable of observing and recording multiple type health data, including weight, location, heart rate, blood pressure and user-context information. Also, many studies[32]–[35]begin to use smartphone to collect human emotion and behavior data by specific mobile applications. So far, these sensory techniques are relatively technically and functionally sophisticated in manually controlled environments. But designing cost-effective and non-invasive wearable devices is demanding and challenging. Many researches[36]–[38]focus on developing some novel accurate, reliable cost-effective and non-invasive sensing techniques for an automatic collection of human health data in IoT based uncontrolled environments

The networking layer for PHS is responsible to connect all devices in sensory layer together and allow personalised health data to be collected, stored, transmitted, shared and aggregated under IoT infrastructures. Also, it provides interoperability and security needed in the context of IoT for healthcare. Riazul Islam *et.al* [39] has reviewed a state-of-the art of IoT healthcare network with three issues: topology, architecture and platform. Each issue has become one of the vital research sub-stream in the IoT enabled PHS. Traditional IoT topology for PHS refers to the representation, configuration and deployment of different health sensor elements in an IoT healthcare network, such as P2P [40], Star [41] and Mesh [42]. As the growth of connected devices and sub-networks, one key research issue of IoT topology for PHS is how to transfer the heterogeneous static and mobile devices into hybrid computing grids. Regarding IoT architectures for PHS, many previous studies have used IPv6 [43] or 6LoWPAN [43] systems as a basis IoT structure, which can enhance the quality of data [46] transmission and extend the range of healthcare services with mobility and scalability [47]. Now, in order to support more standards for interoperation, the service-oriented architecture (SOA) [46] has been proposed and validated by many researchers as a promising solution in IoT enabled PHS. Under SOA, a number of standards have been built to support the needs of interoperability, like Extensible Markup Language (XML), Simple Object Access Protocol (SOAP), etc. Some studies [43], [48] investigate the issues of cost, risk and profit in implementing SOA for large-scale IoT enabled healthcare systems. Apart from above two issues in networking layers, designers also need to address factors such as network management technologies for heterogonous networks (such as fixed, wireless, mobile, etc.), energy efficiency in networks, QoS requirements, service discovery and retrieval, data and signal processing, security, and privacy. Particularly, since personalised health information is relatively sensitive for users, any inappropriate disclosure may violate user privacy. The work in studying security and privacy for IoT enabled PHS has triggered many solutions, like reliable routing [49], cryptographic scheme [50], privacy-preserving health data aggregation [48],

The processing layer of IoT enabled PHS targets at designing useful computational methodologies for processing a variety of complex health related data with aiming quality. The early work in mobile health focuses on developing specific algorithms for some diseases related data rather than general methods handling both health and medical data. For instance, Acampora *et. al*[39] reviewed a number of ambient intelligence algorithms in healthcare regarding five applications: activity recognition, behavioral pattern discovery, anomaly detection, and decision support. But now in the IoT enabled PHS, the key role of specific application is mostly categorized into the application layer, the study focus of data processing layer here has transferred to generic algorithms to improve the accuracy and validity of health data and or new data analytic tools to facilitate scalable, assessable and sustainable data structure. So this paper will summarize data processing algorithms for IoT enabled PHS into three key parts: data driven approaches, knowledge-based approaches and hybrid approaches. More specifically, data driven approaches mainly contain supervised learning, semi-supervised learning and un-supervised learning methods; knowledge-based methods cover modelling and semantic reasoning approaches; hybrid approaches are a combination of above two types of approaches by integrating machine learning into knowledge reasoning. The section III.C will provide a detailed description of utilisation of these data processing approaches into IoT enabled healthcare data analytic.

The role of application layer in IoT enabled PHS is mainly to provide high quality services and easy-to-use interfaces to end users. As mentioned before, previous mobile health researches do not consider application as an individual layer in healthcare, and combine the interface or usability into algorithm layer. So their research focuses on evaluating if entire system or new algorithms have practical effect or help on medical care. In the IoT environment, PHSs are used by a large-scale population so that the scope of research in application layer has expanded into more wide areas, including healthcare service discovery, healthcare service composition, healthcare platform API, human-computer-interaction in healthcare, etc. Moreover, studies of application layer in IoT enabled PHS also covers different kinds of healthcare applications in academia and industry, like continuous monitoring, assisted living, therapy and rehabilitation, persuasive wellbeing, Emotional Wellbeing and Smart Hospitals, etc.

Mobile technologies nowadays play essential roles in healthcare monitoring and services. These technologies include mobile phones, personal digital assistants (PDAs), mobile cameras (e.g., *SenseCam*), smart watches, etc. As most of mobile devices are embedded a variety of inertial sensors (e.g., accelerometer, gyroscopes, etc.) and biomedical sensors (skin temperature, heart rate, etc.), they are designed for providing personalised and continuous cares for users. For example, many mobile products (e.g., Fitbit) and applications (e.g., Moves) have been released for the long term record and collection of personal lifelogging physical activity [51]. Some devices involve in patient's self-management and interventions [1]. Other applications that make use of inertial sensors are capable of falling detections and thus avoid undesirable consequences [59]

## III. Key Enabling Technologies in IoT enabled PHS

### A. Sensing and Identification Technologies

Sensing and identification technologies target at recognizing physical objects and gathering human health information from sensors, tags, etc. The prominent development of low-cost and small-in-size wearable sensor such as inertial sensors (e.g., accelerator, gyroscope or barometric pressure sensors) and physiological sensors (e.g., spirometer, skin temperature sensor or blood pressure cuff), as well as wearable devices (e.g., fitness band or mobile phone) has facilities the process of measuring attributes related to individuals and their soundings. As a major risk measure for chronic diseases, a number of wearable sensors are studied by researchers for monitoring daily healthcare. Table 2 shows a list of wearable and ambient sensor categories.

*Inertial sensors* are small-scale MEMS devices, which usually fit for measuring human physical activity. They are placed on different parts of body [24]. Accelerometers can measure degree of position changes of human motion; Gyroscopes are generally combined with accelerometers for measuring rotational movements in keen joint rehabilitations [74]. Applying both inertial sensors also enable accurately detecting a specific type of human motion and behaviors, such as bend knees, descend stairs [18], ascend stairs or turning [57]. Their applications cover gait rehabilitation, joint pathology [5],stork [10], Parkinson's disease [57] and fall detection [53].Similarly, pressure sensors, along with accelerometers are also useful in monitoring stairs behaviors[62] and fall detection [63] owning to their relationship between sensory readings and altitude. Magnetic field sensor is another type of inertial sensor that can be abled to be placed close to measurement location for achieving high spatial resolution to detect human's direction. For instance, in order to recognize a activity of "watching TV", a study [64] presents that a magnetometer based system with combining accelerometers and indoor localization can tell that a person is facing to a television.

*Physiological sensors* are mainly designed for measurement of specific health related personal data, like heart rate, temperature. In order to ensure high accuracy of measurements, physiological sensors used to be relatively expensive and are mostly used in clinics. Now, advance sensory techniques boost the design and development of a large amount of cost-effective physiological sensors. For instance, Electrocardiogram (ECG) for heart rate monitoring has been broadly contributed to physical activity recognition and monitoring [65] and daily patients [61] health monitoring. More importantly, these physiological devices are feasible to be used in out-of-hospital conditions, can enable a health data transmission through Internet.

*Image sensor* in IoT enabled PHS usually indicate a camera that is utilised for recording and understanding human activities, emotions or other contexts by using image or video processing techniques. Typical image sensor related IoT enabled PHS cases[100] include *SenseCam, Sony Xperia eye,* etc. Their developers use a low cost wearable camera as visual life-logger for recording user daily activity related image sequences. With support of location data and image annotation, these tools can effectively recognize users' daily activity and behavior, further results in improved and innovative home care solution for older people. But compared with other sensor technologies, image sensor technology for healthcare requires a much higher level of privacy protection. Especially in a lifelogging mode of IoT enabled PHS, how to store and protect high volume of image data is a big challenge.

Another key trend in IoT related sensing technology is that the appearance of many commercial wearable products and mobile applications enables a possibility of collecting multi-types of personal health data with hybrid sensors. The most famous mobile apps, such as *Moves* [68], are based on smartphone 3D accelerometer data and GPS information. It allows tracking user movement activities including location, distance and speed. The wearable products, such as *Fitbit Flex* [69], *Nike+ Fuelband* [70], *Withings* [71], are all wristband devices that record steps count, distance, and calories burnt. These health related data are synchronized to mobile phone via blue-tooth, and further used in relevant mobile applications.

**Table .2. Typical sensing and identification technologies**

| Sensor category | Sensor subcategories | Sensor examples | Measured parameters |
|---|---|---|---|
| Wearable sensors | Inertial sensors | Accelerometer [72] | Linear acceleration of movement |
| | | Gyroscopes [55] | Angular rotational velocity |
| | | Pressure sensors [62] | Object's altitude |
| | | Magnetic field sensors [73] | Location of higher spatial resolution |
| | Location sensors | GPS [74] | Outdoor locations |
| | Physiological sensors | Blood pressure cuff [75] | Systolic and diastolic blood pressure |
| | | Electrocardiogram (ECG) [27] | Rhythm and electrical activity of the heart |
| | | Spirometer [76] | Expiration, flow rate and lung volume |
| | | Electrooculography (EOG) [77] | Eye movement |
| | | galvanic skin response (GSR) [15] | Skin surface temperature |
| | Image sensors | SenseCam [66] | Photographs of daily living |
| Ambient sensors | Environment sensors | Thermometer [78] | Indoor/outdoor temperature |
| | | Hygrometer [79] | Indoor/outdoor humidity |
| | Binary sensors | Window contact [80] | Window open/close state |
| | | Door contact [80] | Door open/close state |
| | | Light switch [80] | light on/off state |
| | | Remote control switch [80] | Remote control on/off state |
| | Location sensors | Infra-red [81] | Indoor localization |
| | | Zigbee [82] | Indoor localization |
| | | Active RFID [3] | Indoor localization |
| | Tags | RFID tags [83] | Objects individual interact with |
| | | NFC tags [84] | Objects individual interact with |

Apart from above wearable sensor technology, ambient sensor technology is also an important stream for IoT enabled PHS, as shown in Table.2. Typical ambient sensors include environment sensors, binary sensors, location sensors, etc. Their appliances focus on smart-home or smart-hospitals. Considering that the attention of this paper is to review technologies for personalised healthcare system, we mainly summarize key wearable sensing technologies for IoT enabled PHS in this paper.

### B. *Networking Techniques*

Typically, networking layer in IoT applications contains a wide field of concepts and techniques, such as communication and location technologies, topologies, architecture, security and privacy, etc. However, for IoT enabled healthcare applications, a significant obstacle is that the majority of existing IoT enabled PHS system has limited permission on accessing and connecting hospital systems due to severe considerations on patients record and data. Thus, existing end-points of networking layer in IoT enabled PHS mostly rely on a third party server from companies or organizations with similar protocols. Thus, we will mainly concern three research issues mentioned in Section II: topology, architecture, security and privacy.

From classic networking standards perspective, IoT topologies can be categorized into three basic network topologies: p2p[40], star[41] and mesh[42]. Their characteristics, capabilities and behaviors are reflected by five key factors: latency, throughput, fault resiliency, scalability, hops and range. But for IoT enabled PHS, the topology needs to be a heterogeneous computing grids for collecting enormous amount of vital signs and health data, such as blood sugar, physical activity, blood pressure, oxygen saturation, etc. Viswanathan et.al [85] presents a new mobile grid computing topology '*hybrid static/mobile computing grid*' for data- and patient-centric IoT enabled healthcare systems. It transfers the heterogeneous computing and storage capability of static and mobile electronic devices into hybrid computing grids by employing self-optimization and self-healing. Yang et.al [51] also introduces an IoT topology that supports the streaming of ultrasound videos through an interconnected network with worldwide interoperability for microwave access (WiMAX), an internet protocol (IP) network, and a global system for a mobile (GSM) network as well as usual gateways and access service networks. Jara et.al [52] also introduces a topology that considers an intelligent medicine box as a gateway to connect various wearable sensors, health-IoT cloud and heterogeneous network for supporting clinical diagnosis and analysis. The role of gateway in this IoT topology can examine, store and display all collected health data.

Regarding IoT architecture, SoA has been considered as a key technology in integrating heterogeneous systems or devices. In IoT enabled PHS, the design of architecture needs to treat a lot of issues, including architecture style, communication, sensors, web services and health applications, health data processing and protection, etc. Many researchers have explored the role of SoA in e-healthcare systems. For instance, Kart et al. [86] has applied SOA as a foundation to design, implement, deploy and manage health services in a distributed network system. Omar and Teleb-Bendiab [53] developed an experimental e-health monitoring system thatuses an SOA as a model for deploying, integrating, implementing and managing e-health services. The above studies show that SOA is an effective approach for IoT enabled PHS to reach interoperability between heterogeneous devices and deliver cost-effective healthcare services.

Lastly, after collecting diverse health data, security and privacy issues are critically important to IoT enabled PHS. Zhang et al [107] reviews these two issues for mobile healthcare networks from a quality of protection perspective: privacy leakage, secure data access and processing, malicious attacks and misbehavior. In order to solve these issues, a number of researches have been carried out. Zhang et al [55] proposed a priority based health data aggregation method for cloud assisted WBANs. It can aggregate different types of health data within tunable delay requirements, and also protects data and identity privacy during transmission. Zhou and Ren [87] suggest a scheme to securely and efficiently outsource the computationally intensive access control operations of ABE (Attribute Based Encryption) to the shared cloud, thus further providing a fine-grained access control to users' important data. With this scheme, in a high level view, data owners only need to specify access policies on the encrypted data; and their access control can be done automatically by the cloud. For preventing misbehavior detection in IoT enabled PHS, Zhang et al [89] also developed a social-based mobile Sybil detection scheme for exploring mobile user's pseudonym changing behaviors and contact statistics to differentiate Sybil attackers from normal users.

### C. *Data Processing Techniques*

Data processing techniques for healthcare contains a quite wide scope regarding different types and format of data, different size of data, different purpose of applications. So here we only give a brief introduction of computational methodologies for health related data processing mentioned in section II, with a classification of data-driven approaches, knowledge base approaches and hybrid approaches, as shown in Table.3.

**Table .3. Data processing techniques in IoT enabled PHS**

| Category | Sub-Categories | Algorithms | References |
|---|---|---|---|
| Data-driven approaches | Supervised learning | ANNs | [23],[90], [150] |
| | | HMMs | [93]–[100] |
| | | SVM | [34], [96], [42], [111], [123], [124] |
| | | Decision tree | [36], [126]–[130] |
| | Semi-supervised learning | Co-training | [133], [38], [109], [110] |
| | Unsupervised learning | Expectation maximum | [111], [112], [95] |
| | | K-means | [161], [165] |
| Knowledge-based approaches | | Semantic modeling andreasoning | [114]–[116][117] |
| Hybrid approaches | Data-driven+Knowledge-based | | [118],[119] |

#### 1. *Data-driven approaches*

In IoT enabled healthcare field are based on a mechanism that makes use of a large volume of health related data from different subjects for training general models. Regarding the types of training or learning, it can be classified into supervised, semi-supervised and unsupervised algorithms. A number of mainstream of algorithms are reviewed below:

#### 1) *Supervised learning methods*

Dataset is often divided into training sets and testing set in the procedure of conducting supervised learning algorithms. Training dataset, also called labelled data samples is made use for building the prediction model, whilst a testing dataset is for validating the model. For most occasions, larger datasets are used to train models, while smaller ones are for validating the prediction results. Supervised learning are widely and effectively applied in computer-aided systems for activity recognition, clinical decision making and symptom rehabilitations. Typical supervised learning approaches are artificial neural networks (ANN), Bayes networks (BNs), decision tree (DT), support vector machine (SVM), K-near neighbor (KNN), etc. For example, ANNs have been used by many researchers for identifying and classifying different types of human physical activities and diseases diagnostic systems. Gyllensten and Bonomi [64] proposed a feed-forward neural network with 5-fold cross validation to train the data of free-living subjects in daily life from a single accelerator. Nii et al [47] proposed a fuzzified neural network to train ECG data for estimating human physical activity. R. Das et al. [120] build heart disease diagnosis model with multi-layer feedforward neural networks achieving 89.01% accuracy classification. DT also is also a typical algorithm widely used in healthcare applications, especially for physical activity monitoring related disease diagnosis and treatments [108]. Likewise, SVM is capable to address the issue of either wearable sensors for precisely observing abnormal activities [121], or static postures detection for healthcare measurement [102], as well as in clinical outcome classification and prediction (e.g., disease diagnosis) [31]. In recent years, deep learning has gradually became a popular method in medical diagnosis and health state classifications due to its high efficiency and accuracy. Though deep learning techniques are traditional used in medical image analysis, a few works also operate them in terms of sensor signals. Tamilselvan P. et al. [122] applied deep belief network (DBN) constructing a hierarchical layer model with deep network for health diagnosis method. The experiment results outperform traditional machine learning methods like SVM especially in high dimensional data inputs.

To achieve more satisfactory and practical performance, many researches combine different classifiers for the same purpose as standalone classifier, which are efficient to process data from both a single accelerometer [107] and from multiply wearable sensors [25]. For instance, DT and ANN are combined in the study [25] for unconditional physical activity detections, and the results was prominently improved by being replaced every node in DT models with ANN. In the same manner, naïve Bayes classifier was fused into each node of Hidden Markov model (HMM) proposed by [123] for AAL in a context-awareness environment. HMM was incorporated into Gaussian Discriminant Analysis (GDA) classifier presented in [124], achieved a considerably satisfactory result to naïve Bayes and single GDA classifier in accuracy. On the other hand, it is the combination of several algorithms that causes high accumulation of complexity of each classifier. Hence, such hybrid classifier would weaken system performance on capacity and time.

### 2) *Semi-supervised learning methods*

Above supervised learning methods have their advantages on processing data in healthcare or clinical applications. But in practice, labelling every sample in supervised learning methods is quite expensive and requiring lots of human efforts. Some health datasets provided by unknown third party may exclude user annotations. So in these practical cases, semi-supervised or unsupervised learning methods are more popular. Some IoT enabled healthcare studies investigated the performance of applying semi-supervised methods in practical healthcare applications is to only train a small amount of labelled data, and leave a large amount of unlabeled data for an improved feasibility and reduce cost. Co-training is a classic semi-supervised setting that takes advantage of two classifiers independently to train and update data from multi-view using unlabeled samples with high degree of confidence [125]. Stikic et al. [109] made use of accelerometer and infra-red, compared different semi-supervised techniques, found that co-training and self-training methods are the most adaptive methods for physical activity models. Furthermore, En-Co-training is an improved version proposed by Guan et al. [126] which is more flexible for physical activity measurements, since compared to Co-training with two separately strong classifiers, En-Co-training trains data as a whole without requirement for confidence of the labelling of each classifier. The study showed with 40 wearable sensors on the individual's legs, results of static postures and ambulation obtained better performance than supervised methods when 90% samples are unlabeled. [127]

### 3) *Unsupervised learning methods*

A few studies investigated typical unsupervised clustering methods like K-means cluster [111] and Gaussian mixture model (GMM) [128]. For example, Maekawa et al. [128] proposed a probabilistic model employing GMM to calculate the similarity of physical characteristics between a new user and source users and hence find the closest activity pattern. On the other hand, Alshurafa et al. [111] pointed out that GMM is the better algorithm compared to K-means clustering in different levels of activity intensity which would benefit intersubject variability. In addition to these, minority unsupervised learning methods have the aid of Intermediary to analyse abundant data resources from the web rather than directly labelling raw signals collected by the researchers. For instance, the "bag-of-words" model [129] is a text processing technique, while Huỳnh et al. [130] employed in activity observation where a series of sensor data were converted into documentation for inference of different types of activity. As such, sensor-based activity data are regarded as stream of natural language terms to match objects for mining models from the web [131].

## 2. *Knowledge-based approaches*

Knowledge-based approaches represent and transfer knowledge from human expert (e.g., healthcare personnel and medical experts) into computer algorithms to establish computer-aided decision support system. For example, a knowledge-based system can deliver tailored information and advice to patients, carers and family members of the patient, taking decisions that are described in the treatment plan. Equally it can recommend diagnosis and clinical decisions to health personnel who will make changes in medication, and thus significantly improve the quality of live (QoL) for patients of chronic disease and elderly people living independently [1]. Organizational knowledge model construction and rule-based inference are two main stages for carrying out knowledge-based methods. The structure of models is built in a way that allow systems to automatically process reasoning, whilst the inference is made of a set of IF (premise) THEN (action) rules from domain expert.

The knowledge model is expressed in some knowledge representation language or data structure that enable computer to execute the semantic rules. Knowledge-based approaches mainly consist of syntax-based, logic-based and ontology-based approaches. Syntax-based approach makes use of grammar that express the structure based on language modelling. It follows hierarchical structure containing two layers which are HMMs (Hidden Markov Models) and BNs (Bayes Networks) on the bottom and CFGs (Context Free Grammars) on the top. Logic-based method such as description logic describes entities and then make logical rules for high-level reasoning. Among knowledge-based approaches, ontology is the most flexible and used approach in IoT enabled healthcare filed due to its reusability, computational completeness, decidability and practical reasoning algorithms. Its organizational structure for knowledge not only define concepts, properties, and relationships among them, but also supports instance-based reasoning. Some ontology based open resources of AAL systems that can share and reuse domain knowledge are already available such as SOUPA [114], SOPRANO [115], and GAIA [116].

Rules are defined in the form of an implication between an antecedent and consequent based on the structured model. The conditions are specified in the antecedent, and the results of the reasoning are declared in the consequent. Many researches have been conducted detecting ADLs in IoT environment for assisted living using knowledge reasoning. Also, knowledge-based decision support systems have been studied and deployed in various scenarios of remote health monitoring, reminding patients to visit physicians when their conditions are under severe situations. For example, Abidi et al. [132] developed clinical practice guidelines and a decision support system to support family care for breast cancer patients in terms of semantic and logic inference. Riaño et al. [28] used an ontology based approach to develop two personalized procedures for chronical patient healthcare, including anomaly detection, missing data and preventive actions. Another example is shown by Paganelli and Giuli [133] which provided the context semantic reasoning as monitoring system for chronic patients. Thomas et al. [134] made use of asthma treatment guidelines to provide the physician with disease assessment and recommendations on the basis of objective functional patient testing and case based treatment. Martínez-García et al. [135] discussed a knowledge inference engine to support healthcare personnel to help patients manage depression.

### 3. *Hybrid Approaches*

Since the training data samples and labels in nature environment are very difficult to obtain. Although unsupervised and semi-supervised learning methods have their advantages in reducing the requirement of data sample, the immature foundations often lead to erroneous predictions. While ontological methods are incompetent in handling a variety of uncertainties in real healthcare environment. So the combination of both the data-driven and knowledge-based approaches has the potential to make up the respective shortcomings of each other and thus taking advantage of advances in semantic reasoning with probabilistic models. COASR [118] is the typical case of combining two approaches in ADL detection for self-management of elder people at their own homes. Collecting tens of thousands of training data for a large amount ADL classification is almost an impossible task in such environment, but based on mature techniques of classifying a few physical activities, with high level ontological reasoning, allows the issue well studied and application simply conducted. The same principle is also adopted by R. Helaoui et al. [119] for interleaved and concurrent activity recognition (one of the AAL researches) with Markov logic framework and a set of contextual information acquired from ambient sensory data.

## IV. IoT Applications and Case Studies in PHS

While the technologies applied in IoT enabled PHS are still in its early stage, the potential use in industry is rapidly evolving and growing. A lot of research projects and industrial cases related to IoT enabled PHS has been developed and deployed. In this section, we review some successful platforms and applications including European projects, individually national projects and research approaches.

### A. *Physical activity platforms and applications*

*MSP (Mobile sensing platform)* [136] designed a lightweight wearable device placed on the waist to recognize a variety of physical activities and ADLs through connecting to the mobile phone. The standalone device presented in the work was one of the most state-of-the-art techniques in early stage of activity monitoring investigation using wearable sensors. The platform comprises of sensing model, feature processing model and classification model within the version 1.0, 2.0 and 3.0. Accelerometer and microphone are the two distinct sensors for measure different type of activities. The platform version 2.0 resolves some practical issues such as storage, processor and battery life compared with version 1.0. MSP 1.0 and 2.0 implemented supervised training approach and achieve accuracy rate of activity recognition to 83.6% and 93.8%, respectively, while labelled training data is reduced in the version 3.0, and semi-supervised training method is taken to automatically cluster activity patterns. The result of recognition accuracy is also up to 87.4%. The system trains data offline, but provides real-time feedback.

*WISDM (Wireless Sensor Data Mining)* [137] is a typical platform that detects human physical activity based on Android phone sensors placed in one's pocket. Data is from the accelerometer, features are extracted according to the identification of time between signal peaks, and activities of walking, jogging, ascending stairs, descending stairs, sitting and standing are selected in this work due to their repetitive characteristics. Supervised training algorithms are investigated and compared in the system using J48, logical regression, multilayer perceptron and straw man. The result exhibits that ascending and descending stairs are the most difficultly recognized PA. Besides, the work plans to involve more activities and users, as well as carrying the phone in different part of one's body as the results may diverse from phone putting from tops to trousers.

*mHealthDroid (Mobile Health Android)* [138] is an open source framework designed to facilitate the rapid and easy development of biomedical android application which is available on Google Play [139]. The platform is able to collect data from connecting heterogeneous commercial devices (e.g., smart watch, belt and mobile device) for both ambulation and biomedical signals. The system contains communication manager, data storage manager, data processing manager, visualization manager and system manager. Especially, data preprocessing, segmentation, feature extraction and classification using Weka [140] are operated in the data processing manager. It also provides healthcare interventions such as alerts and guidelines. The most important aspect is its extensibility, which supports diverse modes and ways to facilitate new system implementation for time and cost saving. For instance, mDurance[141], a mobile healthcare support system for assessment of trunk endurance, is implemented in terms of the core functionalities of mHealthDroid.

*WearIT@Work* [142]is an European project to investigate wearable computing technology in different areas. In healthcare, it studied gesture determination, including open/close hood, doors and trunk, checking steering wheel, etc. to assist doctors' diagnosis [123]. Multiple small and cost-effective acceleration sensors are distributed on patient's arms for gesture classification. Data dimensionality are reduced by using supervised learning method dynamic time warping (DTW), and hybrid supervised learning is selected as a recognizer. For each accelerometer axis, HMM is exploited for metaclassifier, while its outcomes are sent to a Naïve Bayes model in order to improve the ultimate result. The experiments proved that using fusion of classifiers achieved high accuracy in the condition of extension of sensor network life time.

Apart from some typical projects above, there are also many other successful IoT enabled healthcare applications, like rehabilitation, persuasive wellbeing, emotional wellbeing and smart hospital. For example, Jarochowski et al. [184] propose the implementation of a system, the ubiquitous rehabilitation center, which integrates a Zigbee-based wireless network with sensors that monitor patients and rehabilitation machines. Etiobe [185] is another project devoted to treat child obesity. Its architecture merges ubiquitous, intelligent, and persuasive features for implementing a cyber therapy approach. It is based on virtual and augmented reality, and attempts to persuade children to avoid poor eating habits. The system uses a collection of environmental sensors for capturing important information such as contextual, physiological, and psychological data. McNaney et al. [186] have designed a wearable acoustic monitor (WAM) device, which provides support in various aspects of social and emotional wellbeing by inferring levels of social interaction and vocal features of emotionality. Rodriguez et al. [187] describe development of SALSA, an agent-based middleware to facilitate responding to the particular demands of patients and hospital's personnel.

### B. *Healthcare service with human interaction*

In recent years, self-management services in tele monitoring and AAL settings have been becoming a heated research and application facial point designed for satisfying user's specific requirements to improve the efficiency and success of a therapy (e.g., changing patient's dosage). The systems provide an alternative approach to improving the quality of live (QoL) of the patients through interaction among patients, physicians and caregivers. Such systems are able to deal with a variety of patient conditions using sensor technologies, objective and subjective assessment methods, treatment plans and guidelines, with tailored information and advice being delivered to patients based on their feedbacks. While the procedure of the service is to collect and storage of relevant health data and then send feedback to the patient, which designated the "Closed Loop Principle" [143].

*EMERGE* (Emergency Monitoring and Prevention) [144] targeted on emergency medical services (EMS) system to assist elderly living independently through automatic detection of ADLs in an IoT environment. Data from wrist devices with embedded-in wearable sensors and ambient sensors at home were collected for activity detection as well as vital data measurement. The proposed framework made attempt to classify different types of activities such as short-term emergencies (e.g., fall, helplessness) and long-term clinical assessment (e.g., toilet usage, sleep) with the knowledge-based approach, and highlighted weight as a characteristic to carry out the fuzzy reasoning. Furthermore, relationships between facts are described orderly for the temporal inference. Knowledge-based model is used as an inference agent describes objects and relationships in the sensing layer and hierarchically constructed. The approach was tested by a few elderly people and caregivers in Europe following the close loop principle.

*MOSKUS (Mobile Musculoskeletal User Self-management)* [1], [145]is a to develop a smart ICT solution to support self-management for patients suffering from arthritis, a prevalent and debilitating chronic disease, and thus, saving costs in the health care sector and improving the clinical outcome. A personalized chronic patient's self-management system (CPSMS) proposed in MOSKUS is a knowledge-based decision support and evidential reasoning system that makes use of a set of reasoning rules, providing non-pharmacological treatment plans to assist patients keep better control on the chronic disease and reduce the frequency of hospital visits. The states of self-report (questionnaires) measurements are divided into four categories: High, Medium, Low and None. Due to the imprecise concepts, fuzzy rule reasoning mechanism are defined for the multiple assessment fusion [145] in CPSMS. This platform delivers patient's conditions, medical and behavioural assessments and inference mechanisms for decision recommendations.

*SMART (Self-Management supported by Assistive, Rehabilitation and Telecare Technologies)* [146] is a personalized self-management and monitoring platform for some health conditions namely chronic heart failure, chronic pain and stroke using wearable sensing technologies. The aim of the project is to assist patients maintain their health condition at home through setting life goals based on a number of physical activity tracking outcomes, also to provide a series of feedbacks according to the process of the therapy plan. In order to monitor patients' physical activities, it made use of accelerometers, vital signs like weighing scales and a blood pressure monitor, as well as ambient sensors (i.e., bed sensor, door sensor, etc.) to monitor patient's activities and sleeping pattern, TV usage and food preparation. Data-driven and knowledge-based methods are both adopted in the SMART.

*PIA (Personal IADL Assistant)* [84] is an AAL JP (Ambient Assisted Living Joint Programme) project aiming at assisting elderly people to live independently in their homes and perform daily activities without external help. It uses simple approach that the elderly people can watch instructional videos of how to use modern household equipment through interacting with Near Field Communication (NFC) tags attached on the equipment with their smart devices. There are two main categories of end-users: elderly people and caregivers. Caregivers are healthcare personnel, family or friends, whose responsibility is to record and upload the instructional video and link it to the NFC tags via PIA app. The end-user then use the smart devices (e.g., smart phone or tablet) with the app installed to tap the equipment with the NFC tag attached and then the same video automatically plays. The ontology-based top-down, goal-driven model is developed in PIA that the goals are set as recognition of elder people's ADLs [147].

### C. *CDSS automated prediction and diagnosis*

*PredictAD (Predict Alzheimer's Disease)* [148] is an European research project for developing a standardised and objective solution that would enable an earlier diagnosis of Alzheimer's disease, improved monitoring of treatment efficacy and enhanced cost-effectiveness of diagnostic protocols. The project develops a generic decision support software library and platform with different classification methods behind with a CDSS model composed by data tier for data collection and storage, logic tier for data processing and presentation tier for user interaction and interface. The special point of this CDSS tool is the proposed disease state index (DSI) function and has been tested for efficiently assessing and predicting different diseases.

*METEOR (Methodist environment for translational enhancement and outcomes research)* [149] is an integrated clinical informatics framework that contains a data and logic storage EDW (enterprise data warehouse) and a clinical outcome prediction tool SIA (software intelligence and analytics) for physicians, caregivers and other clinical staff. The system is also designed to remotely monitor and control the patient's physical state from data collection of blood pressure, spirometry, pulse oximetry, temperature, etc. in the way of communications media like web browser and thus provide medical interventions and reminders. The whole engine integrates many key techniques like service-oriented architecture (SOA) and JBoss application server (JBoss AS) where manage reasoning rules extracted from electronic health record (EHR). Also, the framework is also applied in COPD patient remote monitoring, showing its feasibilities and universalities.

## V. Research Challenges and Future Trends

While empowering the utility of IoT enabled technologies in personalised healthcare has huge potential benefits, it is still broadly agreed that the IoT technologies are in their infancy and face many challenges due to the need of cost-effective sensing technologies, advanced algorithms of processing life-logging data, methods of coping with uncontrolled environment, high volume of data set, security and privacy, etc. Future efforts are required to address these challenges and examine of availability of existing PARM technologies to ensure a good fit in the IoT environment.

### A. *Technical Challenges*

**Cost effective and non-obtrusive wearable sensing**: While existing sensing technologies have made a great progress in the last decade, it still limits to long-term healthcare monitoring in the free living environment, as even only a small single sensor attached on a certain part of the body is still uncomfortable for permanent monitoring. While wearable devices have been proven its popularity among general users, their majority usages are limited in the fitness fields. The products simply provide processed measurements (e.g., steps, distance or calories) so that suffer from further data processing. Raw sensor data can be directly acquired from mobile phone, but because of diversity of life pattern and environmental impacts, personal data from individual wearable device exhibits remarkable uncertainty in the natural environment such as battery, capacity issues and placed positions. The results are widely divergent when the mobile phone is put in the pants pocket from handbags. Particularly that inertial sensors are sensitive to any changes in position and orientation. Thus, so far, existing wearable sensing technologies are limited in terms of their size, fast response, continuous monitoring capability, wireless data transmission, and non-obstructive user experience. Moreover, there is usually a tradeoff between high quality and low cost of developing sensing technologies. The idea candidate of future sensing technologies for IoT enabled PHS should be a tiny sensor into personal daily use items, including but not limited to clothing, watches, glasses, shoes, belts, and so on. Moreover, for many chronic disease monitoring, non-obstructive sensing devices are key to success of IoT enabled PHS, and will potentially bring a lot of convenience to patients.

**Secured and Trustful mobile health platform**: Any healthcare related applications must consider various security and privacy issues. In many IoT enabled PHS applications, since health information (e.g., phenomena, health condition, emergency) is relatively sensitive for users, any inappropriate disclosure may violate user privacy and even result in property loss. Users may also concern about their critical health data being tampered with when their health data are stored in untrusted servers or places. Also some malicious attackers misbehave in IoT based health systems to disrupt the effectiveness or mislead other users' preferences. Thus, how to provide appropriate security and privacy protections in IoT enabled PHS platform is still a challenging issue. Without good schemes to protect user's privacy, users may not accept IoT enabled healthcare applications. Another important issue is that the costs of security protections vary with users' diverse demands, and may impact users' experiences of mobile health applications. For example, complicated encryption techniques may offer users more security guarantees but with higher computational overheads and latency than lightweight ones. To satisfy users' diverse security requirements and balance the trade-off between the performance and security protections, quality of protection has become a newly emerging security concept that allows applications to seamlessly integrate adjustable security protection.

**Effective data validation in healthcare**: In a IoT enabled PHS environment, as we mentioned before, personal health data from individual wearable device exhibits remarkable uncertainty in the natural environment. How to validate these data in longitudinal healthcare cases is very challenging. As the exponential growth of mobile healthcare market, numerous similar wearable products have been developed, which will significantly increase the heterogeneity and diversity of devices connected in IoT based personalized healthcare systems. Effective validating these health data from heterogeneous devices in IoT enabled personalized healthcare environment is difficult, and needs more advanced intelligent algorithms.

**Intelligent data processing and analytic in healthcare**: In terms of traditionally adaptive models for different people with different physical states, all data-based approaches require large number of samples for model training, in which supervised learning methods need to be set appropriate categories ahead of time, and each sample needs to be labelled. In addition, in the cases of abnormal behavior alerts for the elderly (e.g., falling or faint), the systems must enable prompt interaction with users and caregivers. Considering limitations of existing sensing devices which algorithms are normally implemented on the remote server, choosing lower complexity of algorithm may suffice to the circumstances. Also, for the life-logging physical activity monitoring environments like symptom analysis from long-term daily activity record, precise offline algorithms tend to be more functional. Lastly, only a few attentions are devoted to training healthcare model from the sensor signals in naturalistic or semi-naturalistic environment. Semi-supervised and unsupervised approaches are more eligible in real life with many uncertainties, and thereby to resolve the complexity and accuracy of the algorithms is a challenging topic can be further investigated.

**Monitoring and changing individual human behaviour in healthcare**: In traditional model of healthcare, a reactive system that treats acute illnesses after the fact is recently evolving with IoT technologies to one more centred on patients, prevention, and the ongoing management of chronic conditions. Thus, it is highly important to effectively monitor and change individual behaviour with IoT enabled personalised healthcare systems, which requires a close collaboration between technical experts and clinicians. This need poses a variety of new research issues. Firstly, how to integrate behaviour change into new healthcare delivery models with IoT enabled PHS is a big issue. Many old health systems are putting increased emphasis on primary care, especially through the use of integrated care delivery models designed to improve the health of the population. To succeed, these new models must extend their reach outside of the four walls of a clinician's office so that they can support patient behavior change beyond traditional clinician-patient interactions. This requires new capabilities, including clinical workflow tools to support patient targeting, care alerts sent to both clinicians and patients, enhanced communication and care management support for patients, and remote monitoring. Clinicians must adopt a patient-centered approach when they interact with patients, one that focuses on understanding the whole person and their barriers to change. Secondly, it is worthy to study of utilizing remote and self-care-oriented technologies to enhance the communication between patients and clinicians. Frequent, real-time communication and feedback are important in supporting change efforts. Traditional models of care delivery have, at their core, face-to-face interactions between clinicians and patients. New technologies, however, are augmenting this interaction model and fundamentally transforming the ways in which clinicians deliver and individuals and their friends and family consume care. Mobile apps, for example, can facilitate tracking and monitoring.

### B. *Future Research Trends*

**Sensing interoperability:** multiple sensors with different features often coexist in a single biometric system. While sensor interoperability refers to the ability of the system to merge and adapt data from different types of sensor and device. In IoT-based PHS, such interoperability is especially distributed in network layer and processing layer. Firstly, the battery life and bandwidth overhead for low power sensor nodes is a still challenge. Second, due to different types of sensors have diverse characteristics such as frequency, as such, many approaches and biomedical platforms have been proposed for sensing interoperability. However, almost every biomedical sensor has its interoperability issues, few systems so far are able to handling with raw sensor data and feature extractions in pre-processing level in real, and thus expected to provided more practical and feasible approaches.

**Lifelogging Mode:** One key feature of IoT environment is that the collection of life-logging data becomes possible. It means that daily health data are monitored and accessed continuously and constantly in a life-long term. Due to limited memory and power resource in affordable wearable devices, life-logging physical activity data will not be milliseconds-based raw sensory signal, but minutes/hours-based segmented set. The changed typed of raw data leads to different features in a simple unchanged subject of physical activities. Existing researches cannot apply the same machine learning algorithms into these new features for equivalently high accuracy. Thus, how to effectively transfer these available machine learning algorithms into these new features in life-logging health related data, how to explore new feasible algorithms for training these life-logging data set, what kind of features in these life-logging data potentially leads to the best accuracy, etc. are all valuable research topics in this area.

**Uncontrolled environment:** Another feature of IoT enabled PHS is to face to completely uncontrolled environment. It follows a global trend of population aging, which requires the transformation of traditional hospital based healthcare services to patient empowered home based healthcare services. In this case, the future trend of using IoT technologies in PHS will focus on completely real life or namely uncontrolled environments. However, existing health related data analyzing methods were mostly set up and verified in lab or experimental scenarios for the purpose of improving recognition accuracy, and suffer from application in unconditional environments (i.e., outdoor, real home). The reason for that is lying on the two crucial but inevitable issues: short-battery or poor capacity of devices and time-consuming of running machine learning algorithms. Moreover, the diverse life pattern of individual person will cause huge uncertainty on personal health data in uncontrolled environment. People performs physical activities in varied manners owning to different age, gender, weight, etc. Hence, a specific recognition model fits one group of people may not fit another one. Thus, how to achieve high accuracy and stability of health data processing using IoT technologies in uncontrolled environment is of interest to many researchers in future.

**High volume of data:** The heterogeneous devices connected in IoT environments and life-logging collection of physical activity data will be driving major expansion in big data of personal health information. These data contain not only a sheer volume of long-term personal lifestyle information, but also complex, diverse and rich context of other health information. The uncertainty of these data will be much higher than physical activity data training by classic machine learning methods in healthcare fields. Effectively and efficiently improving validity of these health related data and exploring useful knowledge becomes a difficult task. Therefore, research work on how to explore these big health related data under IoT environments for bringing intelligence for more solid clinical decision-making and policy formulation will be significance.

**Security and Privacy:** The architecture of IoT environment is supposed to be a very complicated heterogeneous network. IoT enabled PHS may be a specific application or service in the entire IoT environments. But, the personalised health data will be stored and managed into the server of IoT systems. The typical issues of security and privacy in IoT networking architecture will be naturally inherited to IoT enabled PHS applications. Compared to existing commercial wearable devices with data protection scheme on their standalone server like Fitbit, etc. protecting privacy and security in the IoT environments is more serious and difficult since the number of potential attack vectors on IoT entities is obviously much larger. So more research work on how to protect security and privacy needs to be carried out in healthcare using IoT technologies.

## VI. CONCLUSIONS

Internet of Things paradigm represents the vision of the next wave of ICT revolution. IoT enabled technology in PHS will enable faster and safer preventive care, lower overall cost, improved patient-centered practice and enhanced sustainability. IoT enabled PHS have the potential to enhance our everyday life in many different aspects and, in particular. In this survey, we explored the application of IoT in healthcare from various perspectives. We reviewed the existing state-of-the-art technologies for IoT enabled healthcare applications. From a different perspective, we discussed current technology and infrastructure, such as sensing, networking and data processing technologies. More importantly, we provided a high level description of various IoT enabled healthcare applications. But, we are aware that the goals set up for IoT in healthcare are not easily reachable, and there are still many challenges to be faced and, consequently, this research field is getting more and more impetus. Researchers with different backgrounds are enhancing the current state of the art of IoT in healthcare by addressing fundamental problems related to human factors, intelligence design and implementation, and security, social, and ethical issues. Asa result, we are confident that this synergic approach will materialize the complete vision of IoT and its full application in healthcare and human wellbeing.

## REFERENCES


[1] J. Qi, L. Chen, W. Leister, and S. Yang, "Towards Knowledge Driven Decision Support for Personalized Home-Based Self-Management of Chronic Diseases," *2015 IEEE 12th Intl Conf Ubiquitous Intell. Comput. 2015 IEEE 12th Intl Conf Auton. Trust. Comput. 2015 IEEE 15th Intl Conf Scalable Comput. Commun. Its Assoc. Work.*, pp. 1724–1729, 2015.

[2] P. Rashidi, M. Ieee, A. V Vasilakos, and S. M. Ieee, "A Survey on Ambient Intelligence in Healthcare," vol. 101, no. 12, 2013.

[3] P. Yang, W. Wu, M. Moniri, and C. C. Chibelushi, "Efficient object localization using sparsely distributed passive RFID tags," *IEEE Trans. Ind. Electron.*, vol. 60, no. 12, pp. 5914–5924, 2013.

[4] P. Yang and W. Y. Wu, "Efficient Particle Filter Localization Algorithm in Dense Passive RFID Tag Environment," *Ieee Trans. Ind. Electron.*, vol. 61, no. 10, pp. 5641–5651, 2014.

[5] E. G. Spanakis, "MyHealthAvatar : personalized and empowerment health services through Internet of Things technologies MyHealthAvatar : personalized and empowerment health services through Internet of Things technologies," no. August, 2015.

[6] P. Klasnja and W. Pratt, "Healthcare in the pocket: Mapping the space of mobile-phone health interventions," *J. Biomed. Inform.*, vol. 45, no. 1, pp. 184–198, 2012.

[7] L. Catarinucci, D. De Donno, L. Mainetti, L. Palano, L. Patrono, M. Stefanizzi, and L. Tarricone, "An IoT-Aware Architecture for Smart Healthcare Systems," *IEEE Internet Things J.*, vol. 4662, no. c, pp. 1–1, 2015.

[8] Y. Liang, X. Zhou, Z. Yu, and B. Guo, "Energy-Efficient Motion Related Activity Recognition on Mobile Devices for Pervasive Healthcare," *Mob. Networks Appl.*, vol. 19, no. 3, pp. 303–317, 2014.

[9] Z. Deng, P. Yang, Y. Zhao, X. Zhao, and F. Dong, "Life-Logging Data Aggregation Solution for Interdisciplinary Healthcare Research and Collaboration," *2015 IEEE Int. Conf. Comput. Inf. Technol. Ubiquitous Comput. Commun. Dependable, Auton. Secur. Comput. Pervasive Intell. Comput.*, pp. 2315–2320, 2015.

[10] D. Naranjo-Hernández, L. M. Roa, J. Reina-Tosina, and M. Á. Estudillo-Valderrama, "SoM: A smart sensor for human activity monitoring and assisted healthy ageing," *IEEE Trans. Biomed. Eng.*, vol. 59, no. 12 PART2, pp. 3177–3184, 2012.

[11] B. Perriot, J. Argod, J. L. Pepin, and N. Noury, "Characterization of Physical Activity in COPD Patients: Validation of a Robust Algorithm for Actigraphic Measurements in Living Situations," *IEEE J. Biomed. Heal. Informatics*, vol. 18, no. 4, pp. 1225–1231, 2014.

[12] B. G. Lee, B. L. Lee, and W. Y. Chung, "Mobile healthcare for automatic driving sleep-onset detection using wavelet-based EEG and respiration signals," *Sensors (Basel).*, vol. 14, no. 10, pp. 17915–17936, 2014.

[13] E. Sazonov, S. Member, N. Hegde, S. Member, R. C. Browning, E. L. Melanson, and N. A. Sazonova, "Posture and Activity Recognition and Energy Expenditure Estimation in a Wearable Platform," vol. 19, no. 4, pp. 1339–1346, 2015.

[14] J. Merilahti, P. Viramo, and I. Korhonen, "Wearable monitoring of physical functioning and disability changes, circadian rhythms and sleep patterns in nursing home residents," *IEEE J. Biomed. Heal. Informatics*, vol. 2194, no. c, pp. 1–1, 2015.

[15] F. Sun, C. Kuo, H. Cheng, S. Buthpitiya, P. Collins, and M. Griss, "Activity-aware Mental Stress Detection Using Physiological Sensors," *Mob. Comput. Appl. Serv.*, vol. 76, pp. 1–20, 2012.

[16] Y. Nam, S. Rho, and C. Lee, "Physical activity recognition using multiple sensors embedded in a wearable device," *ACM Trans. Embed. Comput. Syst.*, vol. 12, no. 2, pp. 1–14, 2013.

[17] S. Reddy, M. Mun, J. Burke, D. Estrin, M. Hansen, and M. Srivastava, "Using mobile phones to determine transportation modes," *ACM Trans. Sens. Networks*, vol. 6, no. 2, pp. 1–27, 2010.

[18] I. P. I. Pappas, M. R. Popovic, T. Keller, V. Dietz, and M. Morari, "A reliable gait phase detection system," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 9, no. 2, pp. 113–125, 2001.

[19] H. Zhou, H. Hu, and S. Member, "Reducing Drifts in the Inertial Measurements of Wrist and Elbow Positions," *IEEE Trans. Instrum. Meas.*, vol. 59, no. 3, pp. 575–585, 2010.

[20] D. M. Karantonis, M. R. Narayanan, M. Mathie, N. H. Lovell, and B. G. Celler, "Implementation of a real-time human movement classifier using a triaxial accelerometer for ambulatory monitoring.," *IEEE Trans. Inf. Technol. Biomed.*, vol. 10, no. 1, pp. 156–167, 2006.

[21] A. M. Khan, Y. K. Lee, S. Lee, and T. S. Kim, "Accelerometer's position independent physical activity recognition system for long-term activity monitoring in the elderly," *Med. Biol. Eng. Comput.*,

vol. 48, no. 12, pp. 1271–1279, 2010.
[22] a. Purwar, D. D. J. D. Do Jeong, and W. Y. C. W. Y. Chung, “Activity monitoring from real-time triaxial accelerometer data using sensor network,” *2007 Int. Conf. Control. Autom. Syst.*, pp. 2402–2406, 2007.
[23] J. Staudenmayer, D. Pober, S. Crouter, D. Bassett, and P. Freedson, “An artificial neural network to estimate physical activity energy expenditure and identify physical activity type from an accelerometer,” no. 17, pp. 1300–1307, 2009.
[24] P. H. Veltink, H. J. Bussmann, W. de Vries, W. J. Martens, and R. C. Van Lummel, “Detection of static and dynamic activities using uniaxial\naccelerometers,” *IEEE Trans. Rehabil. Eng.*, vol. 4, no. 4, pp. 375–385, 1996.
[25] M. Ermes, J. Pärkkä, J. Mäntyjärvi, and I. Korhonen, “Detection of daily activities and sports with wearable sensors in controlled and uncontrolled conditions,” *IEEE Trans. Inf. Technol. Biomed.*, vol. 12, no. 1, pp. 20–26, 2008.
[26] L.-J. Kau and C.-S. Chen, “A smart phone-based pocket fall accident detection, positioning, and rescue system.,” *IEEE J. Biomed. Heal. informatics*, vol. 19, no. 1, pp. 44–56, 2015.
[27] T. Pawar, N. S. Anantakrishnan, S. Chaudhuri, and S. P. Duttagupta, “Impact of Ambulation in Wearable-ECG,” *Ann. Biomed. Eng.*, vol. 36, no. 9, pp. 1547–1557, 2008.
[28] D. Riaño, F. Real, J. A. López-Vallverdú, F. Campana, S. Ercolani, P. Mecocci, R. Annicchiarico, and C. Caltagirone, “An ontology-based personalization of health-care knowledge to support clinical decisions for chronically ill patients,” *J. Biomed. Inform.*, vol. 45, no. 3, pp. 429–446, 2012.
[29] S.-D. Bao, Y.-T. Zhang, and L.-F. Shen, “Physiological signal based entity authentication for body area sensor networks and mobile healthcare systems.,” *Conf. Proc. ... Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. IEEE Eng. Med. Biol. Soc. Annu. Conf.*, vol. 3, pp. 2455–8, 2005.
[30] B. Obermaier, C. Guger, C. Neuper, and G. Pfurtscheller, “Hidden Markov models for online classification of single trial EEG data,” *Pattern Recognit. Lett.*, vol. 22, no. 12, pp. 1299–1309, 2001.
[31] S. Chandaka, A. Chatterjee, and S. Munshi, “Cross-correlation aided support vector machine classifier for classification of EEG signals,” *Expert Syst. Appl.*, vol. 36, no. 2, pp. 1329–1336, 2009.
[32] P. BW, R. WJ, J. Pandya, M. ME, D. B. M, A. WB, and M. Pahor, “Exercise and depressive symptoms: a comparison of aerobic and resistance exercise effects on emotional and physical function in older persons with high and low depressive symptomatology.,” *Journals Gerontol. Ser. B-Psychological Sci. Soc. Sci.*, vol. 57, no. 2, pp. P124-32, 2002.
[33] P. Salovey, a J. Rothman, J. B. Detweiler, and W. T. Steward, “Emotional states and physical health.,” *Am. Psychol.*, vol. 55, no. 1, pp. 110–121, 2000.
[34] K. Oh, H.-S. Park, and S.-B. Cho, “A Mobile Context Sharing System Using Activity and Emotion Recognition with Bayesian Networks,” *2010 7th Int. Conf. Ubiquitous Intell. Comput. 7th Int. Conf. Auton. Trust. Comput.*, no. Im, pp. 244–249, 2010.
[35] A. Steptoe and N. Butler, “Sports participation and emotional wellbeing in adolescents,” *Lancet*, vol. 347, no. 9018, pp. 1789–1792, 1996.
[36] L. Atallah, B. Lo, R. King, and G. Z. Yang, “Sensor positioning for activity recognition using wearable accelerometers,” *IEEE Trans. Biomed. Circuits Syst.*, vol. 5, no. 4, pp. 320–329, 2011.
[37] L. Bao and S. S. Intille, “Activity Recognition from User-Annotated Acceleration Data,” *Pervasive Comput.*, pp. 1–17, 2004.
[38] B. Longstaff, S. Reddy, and D. Estrin, “Improving Activity Classification for Health Applications on Mobile Devices using Active and Semi-Supervised Learning,” *Pervasive Comput. Technol. Healthc. (PervasiveHealth), 2010 4th Int. Conf.*, pp. 1–7.
[39] S. M. R. Islam, D. Kwak, H. Kabir, M. Hossain, and K.-S. Kwak, “The Internet of Things for Health Care : A Comprehensive Survey,” *Access, IEEE*, vol. 3. pp. 678–708, 2015.
[40] “A Scalable and Self-Configuring Architecture for Service Discovery in the Internet of Things.”
[41] L. Goratti, T. Baykas, T. Rasheed, and S. Kato, “NACRP: A Connectivity Protocol for Star Topology Wireless Sensor Networks,” *IEEE Wireless Communications Letters*, vol. 5, no. 2. pp. 120–123, 2016.
[42] S. Alanazi, J. Al-Muhtadi, A. Derhab, K. Saleem, A. N. Alromi, H. S. Alholaibah, and J. J. P. C. Rodrigues, “On resilience of Wireless Mesh routing protocol against DoS attacks in IoT-based ambient assisted living applications,” *2015 17th International Conference on E-Health Networking, Application and Services, HealthCom 2015*. pp. 205–210, 2016.
[43] S. Imadali, A. Karanasiou, A. Petrescu, I. Sifniadis, and et al, “eHealth Service Support in Future IPv6 Vehicular Networks,” *Future Internet*, vol. 5, no. 3. pp. 317–335, 2013.
[44] A. J. Jara, M. A. Zamora, and A. F. Skarmeta, “Knowledge Acquisition and Management Architecture for Mobile and Personal Health Environments Based on the Internet of Things,” *2012 IEEE 11th International Conference on Trust, Security and Privacy in Computing and Communications*. pp. 1811–1818, 2012.
[45] C. Doukas and I. Maglogiannis, “Bringing IoT and cloud computing towards pervasive healthcare,” *Proceedings - 6th International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing, IMIS 2012*. pp. 922–926, 2012.
[46] F. A. Cummins, “Service-Oriented Architecture,” *Building the Agile Enterprise*. pp. 27–73, 2009.
[47] M. S. Shahamabadi, B. B. M. Ali, P. Varahram, and A. J. Jara, “A network mobility solution based on 6LoWPAN hospital wireless sensor network (NEMO-HWSN),” *Proceedings - 7th International Conference on Innovative Mobile and Internet Services in Ubiquitous Computing, IMIS 2013*. pp. 433–438, 2013.
[48] A. Shaikh, M. Memon, N. Memon, and M. Misbahuddin, “The Role of Service Oriented Architecture in Telemedicine Healthcare System,” *2009 International Conference on Complex Intelligent and Software Intensive Systems*. pp. 208–214, 2009.
[49] M. Sarvabhatla, L. N. Kodavali, and C. S. Vorugunti, “An Energy Efficient Temporal Credential Based Mutual Authentication Scheme for WSN,” *Proceedings - 2014 3rd International Conference on Eco-Friendly Computing and Communication Systems, ICECCS 2014*. pp. 73–78, 2015.
[50] M. Zhao, I. Ho, and P. H. J. Chong, “An Energy-efficient Region-based RPL Routing Protocol for Low-Power and Lossy Networks,” *IEEE Internet of Things Journal*, vol. 4662, no. c. pp. 1–1, 2016.
[51] J. Qi, P. Yang, M. Hanneghan, and S. Tang, “Neurocomputing Multiple density maps information fusion for effectively assessing intensity pattern of lifelogging physical activity,” *Neurocomputing*, 2016.
[52] J. K. Lee, S. Robinovitch, and E. Park, “Inertial Sensing-Based Pre-Impact Detection of Falls Involving Near-Fall Scenarios.,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 4320, no. c, pp. 1–27, 2014.
[53] M. Luštrek and B. Kaluža, “Fall Detection and Activity Recognition with Machine Learning,” *Informatica*, vol. 33, no. 2, pp. 205–212, 2009.
[54] P. Pierleoni, A. Belli, L. Palma, M. Pellegrini, L. Pernini, and S. Valenti, “A High Reliability Wearable Device for Elderly Fall Detection,” *IEEE Sens. J.*, vol. 15, no. 8, pp. 4544–4553, 2015.
[55] H. Dejnabadi, B. M. Jolles, and K. Aminian, “A new approach to accurate measurement of uniaxial joint angles based on a combination of accelerometers and gyroscopes,” *IEEE Trans. Biomed. Eng.*, vol. 52, no. 8, pp. 1478–1484, 2005.
[56] M. El-Gohary and J. McNames, “Shoulder and elbow joint angle tracking with inertial sensors.,” *IEEE Trans. Biomed. Eng.*, vol. 59, no. 9, pp. 2635–41, 2012.
[57] A. Salarian, H. Russmann, C. Wider, P. R. Burkhard, F. J. G. Vingerhoets, and K. Aminian, “Quantification of tremor and bradykinesia in Parkinson’s disease using a novel ambulatory monitoring system,” *IEEE Trans. Biomed. Eng.*, vol. 54, no. 2, pp. 313–322, 2007.
[58] P. a. Costigan, K. J. Deluzio, and U. P. Wyss, “Knee and hip kinetics during normal stair climbing,” *Gait Posture*, vol. 16, no. 1, pp. 31–37, 2002.
[59] B. Coley, B. Najafi, A. Paraschiv-Ionescu, and K. Aminian, “Stair climbing detection during daily physical activity using a miniature gyroscope,” *Gait Posture*, vol. 22, no. 4, pp. 287–294, 2005.
[60] H. Dejnabadi, B. M. Jolles, E. Casanova, P. Fua, and K. Aminian, “Estimation and visualization of sagittal kinematics of lower limbs orientation using body-fixed sensors.,” *IEEE Trans. Biomed. Eng.*, vol. 53, no. 7, pp. 1385–93, 2006.
[61] J. P. Giuffrida, A. Lerner, R. Steiner, and J. Daly, “Upper-extremity stroke therapy task discrimination using motion sensors and electromyography,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 16, no. 1, pp. 82–90, 2008.
[62] a Moncada-Torres, K. Leuenberger, R. Gonzenbach, a Luft, and R.

Gassert, “Activity classification based on inertial and barometric pressure sensors at different anatomical locations,” *Physiol. Meas.*, vol. 35, no. 7, pp. 1245–1263, 2014.

[63] F. Bianchi, S. J. Redmond, M. R. Narayanan, S. Cerutti, and N. H. Lovell, “Barometric pressure and triaxial accelerometry-based falls event detection,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 6, pp. 619–627, 2010.

[64] S. a. Lowe and G. ÓLaighin, “Monitoring human health behaviour in one’s living environment: A technological review,” *Med. Eng. Phys.*, vol. 36, no. 2, pp. 147–168, 2014.

[65] M. Altini, J. Penders, R. Vullers, and O. Amft, “Estimating Energy Expenditure Using Body-Worn Accelerometers: a Comparison of Methods, Sensors Number and Positioning.,” *IEEE J. Biomed. Heal. informatics*, vol. 2194, no. c, pp. 1–8, 2014.

[66] A. I. Journal, E. Berry, N. Kapur, L. Williams, S. Hodges, G. Smyth, J. Srinivasan, R. Smith, B. Wilson, E. Berry, N. Kapur, L. Williams, S. Hodges, G. Smyth, J. Srinivasan, R. Smith, B. Wilson, and K. W. The, “The use of a wearable camera , SenseCam , as a pictorial diary to improve autobiographical memory in a patient with limbic encephalitis : A preliminary report,” vol. 2011, no. April 2016, 2011.

[67] C. Gurrin, Z. Qiu, M. Hughes, and N. Caprani, “The Smartphone As a Platform for Wearable Cameras in Health Research,” *AMEPRE*, vol. 44, no. 3, pp. 308–313, 2013.

[68] “Moves.” [Online]. Available: https://www.moves-app.com/. [Accessed: 14-Oct-2014].

[69] “Fitbit Flex.” [Online]. Available: http://www.fitbit.com/uk. [Accessed: 10-Oct-2014].

[70] “Nike+ Fuelband.” [Online]. Available: http://www.nike.com/gb/en_gb/c/nikeplus-fuelband. [Accessed: 10-Oct-2014].

[71] “Withings.” [Online]. Available: http://www.withings.com/uk/. [Accessed: 15-Oct-2014].

[72] C. V Bouten, K. T. Koekkoek, M. Verduin, R. Kodde, and J. D. Janssen, “A triaxial accelerometer and portable data processing unit for the assessment of daily physical activity.,” *IEEE Trans. Biomed. Eng.*, vol. 44, no. 3, pp. 136–147, 1997.

[73] M. Shoaib, S. Bosch, O. Incel, H. Scholten, and P. Havinga, “A Survey of Online Activity Recognition Using Mobile Phones,” *Sensors*, vol. 15, no. 1, pp. 2059–2085, 2015.

[74] L. Liao, D. Fox, and H. Kautz, “Hierarchical Conditional Random Fields for GPS-Based Activity Recognition,” *Star*, vol. 28, pp. 487–506, 2007.

[75] R. Davies, L. Galway, C. Nugent, C. Jamison, R. Gawley, P. McCullagh, H. Zhang, and N. Black, “A Platform for Self-Management Supported by Assistive, Rehabilitation and Telecare Technologies,” *Proc. 5th Int. ICST Conf. Pervasive Comput. Technol. Healthc.*, pp. 458–460, 2011.

[76] D. Wensley and M. Silverman, “Peak Flow Monitoring for Guided Self-management A Randomized Controlled Trial,” vol. 170, pp. 606–612, 2004.

[77] A. Bulling, J. a. Ward, and H. Gellersen, “Multimodal recognition of reading activity in transit using body-worn sensors,” vol. 9, no. 1, pp. 1–21, 2012.

[78] A. R. Doherty, N. Caprani, C. Ó. Conaire, V. Kalnikaite, C. Gurrin, A. F. Smeaton, and N. E. O. Connor, “Computers in Human Behavior Passively recognising human activities through lifelogging,” *Comput. Human Behav.*, vol. 27, no. 5, pp. 1948–1958, 2011.

[79] C. Sugimoto and R. Kohno, “Wireless Sensing System for Healthcare Monitoring Thermal Physiological State and Recognizing Behavior,” pp. 285–291, 2011.

[80] P. De Toledo and A. Sanchis, “Activity Recognition Using Hybrid Generative/Discriminative Models on Home Environments Using Binary Sensors ˜ *,” pp. 5460–5477, 2013.

[81] A. Sixsmith and N. Johnson, “A Smart Sensor to,” 2004.

[82] H. Jong, S. Hee, K. Ha, H. Chul, W. Chung, J. Young, Y. Chang, and D. Hyun, “Ubiquitous healthcare service using Zigbee and mobile phone for elderly patients,” vol. 8, pp. 193–198, 2008.

[83] R. S. Sangwan, R. G. Qiu, S. K. Member, and D. Jessen, “Using RFID Tags for Tracking Patients , Charts and Medical Equipment within an Integrated Health Delivery Network,” pp. 70–74.

[84] J. Rafferty, C. N.-I. Member, L. C.-I. Member, J. Qi, R. Dutton, A. Zirk, L. T. Boye, M. Kohn, and R. Hellman, “NFC based provisioning of instructional videos to assist with instrumental activities of daily living,” pp. 4131–4134, 2014.

[85] and D. P. H. Viswanathan, E. K. Lee, “Mobile grid computing for data- and patient-centric ubiquitous healthcare,” in *n Proc. 1st IEEE Workshop Enabling Technol. Smartphone Internet Things (ETSIoT)*, pp. 36–41.

[86] “A distributed e-healthcare sys- tem based on the service oriented architecture.”

[87] “Attribute-Based Encryption for Fine-Grained Access Control of Encrypted Data.”

[88] “PHDA: A Priority Based Health Data Aggregation with Privacy Preservation for Cloud Assisted WBANs.”

[89] “Exploiting Mobile Social Behaviors for Sybil Detection.”

[90] Y. Shi, Y. Huang, D. Minnen, A. Bobick, and I. Essa, “Propagation networks for recognition of partially ordered sequential action,” *Comput. Vis. Pattern Recognition, 1992. Proc. CVPR ’92., 1992 IEEE Comput. Soc. Conf.*, p. II--862--II--869 Vol.2, 2004.

[91] M. Li, V. Rozgić, G. Thatte, S. Lee, A. Emken, M. Annavaram, U. Mitra, D. Spruijt-Metz, and S. Narayanan, “Multimodal physical activity recognition by fusing temporal and cepstral information,” *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 18, no. 4, pp. 369–380, 2010.

[92] M. Nii, Y. Kakiuchi, K. Takahama, K. Maenaka, K. Higuchi, and T. Yumoto, “Human activity monitoring using fuzzified neural networks,” *Procedia Comput. Sci.*, vol. 22, pp. 960–967, 2013.

[93] T. V. Duong, H. H. Bui, D. Q. Phung, and S. Venkatesh, “Activity recognition and abnormality detection with the switching hidden semi-Markov model,” *Proc. Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, vol. I, pp. 838–845, 2005.

[94] M. Brand, N. Oliver, and a. Pentland, “Coupled hidden Markov models for complex action recognition,” *Proc. IEEE Comput. Soc. Conf. Comput. Vis. Pattern Recognit.*, pp. 994–999, 1997.

[95] D. Trabelsi, S. Mohammed, F. Chamroukhi, L. Oukhellou, and Y. Amirat, “An Unsupervised Approach for Automatic Activity Recognition Based on Hidden Markov Model Regression,” *IEEE Trans. Autom. Sci. Eng.*, vol. 10, no. 3, pp. 829–835, 2013.

[96] P.-C. Chung and C.-D. Liu, “A daily behavior enabled hidden Markov model for human behavior understanding,” *Pattern Recognit.*, vol. 41, no. 5, pp. 1572–1580, 2008.

[97] Y. Lee, “Activity Recognition Using Hierarchical Hidden Markov Models on a Smartphone with 3D Accelerometer,” *Hybrid Artif. Intell. Syst.*, pp. 460–467, 2011.

[98] P. Natarajan and R. Nevatia, “Coupled hidden semi Markov Models for activity recognition,” *Proc. IEEE Work. Motion Video Comput.*, p. 10, 2007.

[99] T. L. M. Van Kasteren, G. Englebienne, and B. J. A. Kröse, “Activity recognition using semi-Markov models on real world smart home datasets,” *Environments*, vol. 2, pp. 311–325, 2010.

[100] N. Oliver, E. Horvitz, and a Garg, “Layered representations for human activity recognition,” *Multimodal Interfaces, 2002. Proceedings. Fourth IEEE Int. Conf.*, pp. 3–8, 2002.

[101] G. R. Naik, D. K. Kumar, and Jayadeva, “Twin SVM for gesture classification using the surface electromyogram,” *IEEE Trans. Inf. Technol. Biomed.*, vol. 14, no. 2, pp. 301–308, 2010.

[102] Z. He and L. Jin, “Activity recognition from acceleration data based on discrete consine transform and SVM,” *Syst. Man Cybern. 2009. SMC 2009. IEEE Int. Conf.*, no. October, pp. 5041–5044, 2009.

[103] S. Liu, R. X. Gao, D. John, J. W. Staudenmayer, and P. S. Freedson, “Multisensor data fusion for physical activity assessment,” *IEEE Trans. Biomed. Eng.*, vol. 59, no. 3, pp. 687–696, 2012.

[104] J. Pärkkä, L. Cluitmans, M. Ermes, J. Parkka, L. Cluitmans, and M. Ermes, “Personalization algorithm for real-time activity recognition using PDA, wireless motion bands, and binary decision tree.,” *Inf. Technol. Biomed. IEEE Trans.*, vol. 14, no. 5, pp. 1211–1215, 2010.

[105] J. Pärkkä, M. Ermes, P. Korpipää, J. Mäntyjärvi, J. Peltola, and I. Korhonen, “Activity classification using realistic data from wearable sensors.,” *IEEE Trans. Inf. Technol. Biomed.*, vol. 10, no. 1, pp. 119–128, 2006.

[106] J. Yang, “Toward Physical Activity Diary : Motion Recognition Using Simple Acceleration Features with Mobile Phones,” *Proc. 1st Int. Work. Interact. Multimed. Consum. Electron.*, pp. 1–9, 2009.

[107] N. Ravi, N. Dandekar, P. Mysore, and M. M. L. Littman, “Activity Recognition from Accelerometer Data,” *Proc. Natl. …*, pp. 1541–1546, 2005.

[108] B. Logan, J. Healey, M. Philipose, E. M. Tapia, and S. Intille, “A Long-Term Evaluation of Sensing Modalities for Activity Recognition,” *UbiComp 2007 Ubiquitous Comput.*, vol. 4717, pp. 483–500, 2007.

[109] M. Stikic, K. Van Laerhoven, and B. Schiele, “Exploring semi-supervised and active learning for activity recognition,” *2008 12th IEEE Int. Symp. Wearable Comput.*, pp. 81–88, 2008.
[110] Y.-S. Lee and S.-B. Cho, “Activity recognition with android phone using mixture-of-experts co-trained with labeled and unlabeled data,” *Neurocomputing*, vol. 126, pp. 106–115, 2014.
[111] N. Alshurafa, W. Xu, J. Liu, M.-C. Huang, B. Mortazavi, C. Roberts, and M. Sarrafzadeh, “Designing a Robust Activity Recognition Framework for Health and Exergaming using Wearable Sensors.,” *IEEE J. Biomed. Heal. informatics*, vol. 18, no. c, pp. 1–11, 2013.
[112] R. Chavarriaga, H. Bayati, and J. D. R. Millán, “Unsupervised adaptation for acceleration-based activity recognition: Robustness to sensor displacement and rotation,” *Pers. Ubiquitous Comput.*, vol. 17, no. 3, pp. 479–490, 2013.
[113] M. Derawi and P. Bours, “Gait and activity recognition using commercial phones,” *Comput. Secur.*, vol. 39, no. 2, pp. 137–144, 2013.
[114] H. Chen, F. Perich, T. Finin, and A. Joshi, “SOUPA : Standard Ontology for Ubiquitous and Pervasive Applications ∗.”
[115] M. Klein, A. Schmidt, and R. Lauer, “Ontology-Centred Design of an Ambient Middleware for Assisted Living: The Case of SOPRANO,” *Context*, vol. 10, p. 2007, 2007.
[116] A. Ranganathan, R. E. Mcgrath, R. H. Campbell, and M. D. Mickunas, “Use of Ontologies in a Pervasive Computing Environment,” 2003.
[117] A. Gangemi, G. Steve, F. Giacomelli, R. I. Medica, and I. T. Biomediche, “ONIONS : An Ontological Methodology for Taxonomic Knowledge Integration.”
[118] D. Riboni and C. Bettini, “COSAR: Hybrid reasoning for context-Aware activity recognition,” *Pers. Ubiquitous Comput.*, vol. 15, no. 3, pp. 271–289, 2011.
[119] R. Helaoui, “Recognizing interleaved and concurrent activities: A statistical-relational approach,” *Pervasive Comput. Commun. (PerCom), 2011 IEEE Int. Conf. on. IEEE*, pp. 1–9, 2011.
[120] R. Das, I. Turkoglu, and A. Sengur, “Expert Systems with Applications Effective diagnosis of heart disease through neural networks ensembles,” *Expert Syst. Appl.*, vol. 36, no. 4, pp. 7675–7680, 2009.
[121] A. Palaniappan, R. Bhargavi, and V. Vaidehi, “Abnormal human activity recognition using SVM based approach,” *2012 Int. Conf. Recent Trends Inf. Technol.*, pp. 97–102, 2012.
[122] “No TitleFailure diagnosis using deep belief learning based health state classification.”
[123] P. Zappi, C. Lombriser, T. Stiefmeier, E. Farella, D. Roggen, L. Benini, and G. Tröster, “Activity recognition from on-body sensors: Accuracy-power trade-off by dynamic sensor selection,” *Lect. Notes Comput. Sci. (including Subser. Lect. Notes Artif. Intell. Lect. Notes Bioinformatics)*, vol. 4913 LNCS, pp. 17–33, 2008.
[124] M. Brown, T. Deitch, and L. O. Conor, “Activity Classification with Smartphone Data,” pp. 1–5, 2013.
[125] T. Mitchell and A. Blum, “Combining labeled and unlabeled data with co-training,” *Proc. Elev. Annu. Conf. Comput. Learn. theory*, pp. 92–100, 1998.
[126] D. Guan, W. Yuan, Y.-K. Lee, A. Gavrilov, and S. Lee, “Activity Recognition Based on Semi-supervised Learning,” *13th IEEE Int. Conf. Embed. Real-Time Comput. Syst. Appl. (RTCSA 2007)*, no. 1, pp. 469–475, 2007.
[127] V. Garla, C. Taylor, and C. Brandt, “Semi-supervised clinical text classification with Laplacian SVMs : An application to cancer case management,” *J. Biomed. Inform.*, vol. 46, no. 5, pp. 869–875, 2013.
[128] T. Maekawa and S. Watanabe, “Unsupervised activity recognition with user’s physical characteristics data,” *Proc. - Int. Symp. Wearable Comput. ISWC*, pp. 89–96, 2011.
[129] Y. Zhang, R. Jin, and Z. H. Zhou, “Understanding bag-of-words model: A statistical framework,” *Int. J. Mach. Learn. Cybern.*, vol. 1, no. 1–4, pp. 43–52, 2010.
[130] T. Huỳnh, M. Fritz, and B. Schiele, “Discovery of activity patterns using topic models,” *Proc. 10th Int. Conf. Ubiquitous Comput. (UbiComp ’08)*, pp. 10–19, 2008.
[131] P. Palmes, H. K. Pung, T. Gu, W. Xue, and S. Chen, “Object relevance weight pattern mining for activity recognition and segmentation,” *Pervasive Mob. Comput.*, vol. 6, no. 1, pp. 43–57, 2010.
[132] S. R. Abidi, S. Hussain, and M. Shepherd, “Ontology-based modeling of clinical practice guidelines: a clinical decision support system for breast cancer follow-up interventions at primary care settings.,” *Stud. Health Technol. Inform.*, vol. 129, no. Pt 2, pp. 845–9, 2007.
[133] F. Paganelli and D. Giuli, “An ontology-based context model for home health monitoring and alerting in chronic patient care networks,” *Proc. - 21st Int. Conf. Adv. Inf. Netw. Appl. Work. AINAW’07*, vol. 1, no. Iccc, pp. 838–845, 2007.
[134] K. W. Thomas, C. S. Dayton, and M. W. Peterson, “Evaluation of internet-based clinical decision support systems,” *J. Med. Internet Res.*, vol. 1, no. 2, pp. 5–13, 1999.
[135] A. Martínez-García, A. Moreno-Conde, F. Jódar-Sánchez, S. Leal, and C. Parra, “Sharing clinical decisions for multimorbidity case management using social network and open-source tools,” *J. Biomed. Inform.*, vol. 46, no. 6, pp. 977–984, 2013.
[136] T. Choudhury, J. Hightower, A. Lamarca, L. Legrand, A. Rahimi, A. Rea, B. Hemingway, K. Koscher, J. a Landay, J. Lester, and D. Wyatt, “An embedded Activity Recognition system,” *IEEE Pervasive Comput.*, vol. 7, no. 2, pp. 32–41, 2008.
[137] J. R. Kwapisz, G. M. Weiss, and S. a. Moore, “Activity recognition using cell phone accelerometers,” *ACM SIGKDD Explor. Newsl.*, vol. 12, p. 74, 2011.
[138] M. D. Oresti Banos, Rafael Garcia, Juan A. Holgado-Terriza and and C. V. Hector Pomares, Ignacio Rojas, Alejandro Saez, “mHealthDroid: A Novel Framework for Agile Development of Mobile Health Applications,” in *Ambient Assisted Living and Daily Activities*, Springer International Publishing, pp. 91–98.
[139] “mHealthDroid.” [Online]. Available: https://play.google.com/store/apps/details?id=com.mHealthDroid.activitydetector&hl=en_GB. [Accessed: 07-Apr-2014].
[140] M. Hall, E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten, “The WEKA data mining software,” *ACM SIGKDD Explor.*, vol. 11, no. 1, pp. 10–18, 2009.
[141] O. Banos, J. A. Moral-Munoz, I. Diaz-Reyes, M. Arroyo-Morales, M. Damas, E. Herrera-Viedma, C. S. Hong, S. Lee, H. Pomares, I. Rojas, and C. Villalonga, “MDurance: A novel mobile health system to support trunk endurance assessment,” *Sensors (Switzerland)*, vol. 15, no. 6, pp. 13159–13183, 2015.
[142] M. Boronowsky, O. Herzog, P. Knackfuß, and M. Lawo, “wearIT @ work - Towards Real Life Industrial Applications of Wearable Computing investigate ‘ Wearable Computing ’ as a technology dealing with computer systems State-of-the-art,” pp. 1441–1447.
[143] A. Dohr, R. Modre-Opsrian, M. Drobics, D. Hayn, and G. Schreier, “The Internet of Things for Ambient Assisted Living,” *2010 Seventh Int. Conf. Inf. Technol. New Gener.*, pp. 804–809, 2010.
[144] H. Storf, M. Becker, and M. Riedl, “Rule-based activity recognition framework: Challenges, technique and learning,” *Pervasive Comput. Technol. Heal. 2009. PervasiveHealth 2009. 3rd Int. Conf.*, pp. 1–7, 2009.
[145] N. Baha and M. Tolba, “Emerging Trends and Advanced Technologies for Computational Intelligence,” vol. 647, 2016.
[146] Y. Huang, H. Zheng, C. Nugent, P. Mccullagh, N. Black, M. Hawley, and G. Mountain, “Knowledge Discovery from Lifestyle Profiles to Support Self-Management of Chronic Heart Failure,” pp. 397–400, 2011.
[147] J. Rafferty, “Goal Lifecycles and Ontological Models for Intention Based Assistive Living within Smart Environments Goal Lifecycles and Ontological Models for Intention Based Assistive Living within Smart Environments,” no. January, 2015.
[148] J. Mattila, J. Koikkalainen, A. Virkki, M. Van Gils, and L. Jyrki, “Design and Application of a Generic Clinical Decision Support System for Multiscale Data,” vol. 59, no. 1, pp. 234–240, 2012.
[149] M. Puppala, T. He, S. Chen, R. Ogunti, X. Yu, F. Li, R. Jackson, and S. T. C. Wong, “METEOR : An Enterprise Health Informatics Environment to Support Evidence-Based Medicine,” vol. 62, no. 12, pp. 2776–2786, 2015.