



Iman Azimi

# Personalized Data Analytics for Internet-of-Things-based Health Monitoring

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# Personalized Data Analytics for Internet-of-Things-based Health Monitoring

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# Abstract

The Internet-of-Things (IoT) has great potential to fundamentally alter the delivery of modern healthcare, enabling healthcare solutions outside the limits of conventional clinical settings. It can offer ubiquitous monitoring to at-risk population groups and allow diagnostic care, preventive care, and early intervention in everyday life. These services can have profound impacts on many aspects of health and well-being. However, this field is still at an infancy stage, and the use of IoT-based systems in real-world healthcare applications introduces new challenges. Healthcare applications necessitate satisfactory quality attributes such as reliability and accuracy due to their mission-critical nature, while at the same time, IoT-based systems mostly operate over constrained shared sensing, communication, and computing resources.

There is a need to investigate this synergy between the IoT technologies and healthcare applications from a user-centered perspective. Such a study should examine the role and requirements of IoT-based systems in real-world health monitoring applications. Moreover, conventional computing architecture and data analytic approaches introduced for IoT systems are insufficient when used to target health and well-being purposes, as they are unable to overcome the limitations of IoT systems while fulfilling the needs of healthcare applications. This thesis aims to address these issues by proposing an intelligent use of data and computing resources in IoT-based systems, which can lead to a high-level performance and satisfy the stringent requirements.

For this purpose, this thesis first delves into the state-of-the-art IoT-enabled healthcare systems proposed for in-home and in-hospital monitoring. The findings are analyzed and categorized into different domains from a user-centered perspective. The selection of home-based applications is focused on the monitoring of the elderly who require more remote care and support compared to other groups of people. In contrast, the hospital-based applications include the role of existing IoT in patient monitoring and hospital management systems. Then, the objectives and requirements of each domain are investigated and discussed.

This thesis proposes personalized data analytic approaches to fulfill the

requirements and meet the objectives of IoT-based healthcare systems. In this regard, a new computing architecture is introduced, using computing resources in different layers of IoT to provide a high level of availability and accuracy for healthcare services. This architecture allows the hierarchical partitioning of machine learning algorithms in these systems and enables an adaptive system behavior with respect to the user's condition. In addition, personalized data fusion and modeling techniques are presented, exploiting multivariate and longitudinal data in IoT systems to improve the quality attributes of healthcare applications. First, a real-time missing data resilient decision-making technique is proposed for health monitoring systems. The technique tailors various data resources in IoT systems to accurately estimate health decisions despite missing data in the monitoring. Second, a personalized model is presented, enabling variations and event detection in long-term monitoring systems. The model evaluates the sleep quality of users according to their own historical data. Finally, the performance of the computing architecture and the techniques are evaluated in this thesis using two case studies. The first case study consists of real-time arrhythmia detection in electrocardiography signals collected from patients suffering from cardiovascular diseases. The second case study is continuous maternal health monitoring during pregnancy and postpartum. It includes a real human subject trial carried out with twenty pregnant women for seven months.

# Tiivistelmä

Esineiden Internet (Internet of Things, IoT) tulee todennäköisesti mullistamaan tulevaisuuden terveydenhuollon laajentamalla terveydenseurannan perinteisen kliinisen ympäristön ulkopuolelle. IoT-ratkaisut mahdollistavat riskiryhmien terveydentilan jatkuvan monitoroinnin, mahdollistaen samalla diagnostisen hoidon, ennaltaehkäisevän hoidon ja aikaisen puuttumisen osana potilaiden jokapäiväistä arkea. Kyseinen ratkaisu parantaisi terveyden- ja hyvinvointia laaja-alaisesti. IoT-ratkaisut ovat kuitenkin vielä tiensä alussa, joten IoT-sovelluksilla on vielä monia haasteita terveydenhuollon toimialalla. Terveydenhuoltosovellusten laatuvaatimukset kuten luotettavuus ja tarkkuus ovat turvallisuuskriittisiä tekijöitä, sitä vastoin IoT-pohjaiset järjestelmät jakavat resursseja havainnoinnin, kommunikaation ja laskennan kesken, joskin rajoitetusti.

Jotta nämä järjestelmät hyötyisivät toisistaan mahdollisimman paljon, täytyy molempia tarkastella käyttäjänäkökulmasta. Tällöin tulee tarkastella IoT-ratkaisun roolia ja vaatimuksia terveydenseurannan käyttötilannetta. Lisäksi pitää pohtia perinteisen tietokonearkkitehtuurin ja data-analytiikan perinteisten ratkaisujen rajoitteita terveyden ja hyvinvoinnin IoT-ratkaisun puitteissa. Tämän tutkielman tavoitteena on ehdottaa tähän ratkaisuksi tiedon ja laskentaresurssien älykästä hyödyntämistä IoT-järjestelmissä, jotta pystytään saavuttamaan korkea suorituskyky ja täyttämään terveydenhuollon laatukriteerit.

Näitä vaatimusten tarkastelussa, tutkielma pureutuu ensin tyypillisiin kotona ja sairaalassa käytettäviin terveydenhuollon IoT-monitorointiratkaisuihin. Järjestelmiä analysoidaan ja luokitellaan eri käyttöalueiden mukaan käyttäjänäkökulmasta. Kotiseurantaratkaisuisissa keskitytään vanhuksiin, jotka muita ryhmiä enemmän tarvitsevat etäseurantaa ja tukea. Sairaalamonitoroinnissa puolestaan IoT-ratkaisut keskittyvät potilasseurantaan ja sairaalajärjestelmiin. Lisäksi tutkitaan ja pohditaan jokaisen käyttöalueen tavoitteita ja vaatimuksia.

Tämä tutkielma ehdottaa näille vaatimuksille ja terveydenhuollon IoT-pohjaisen järjestelmän tavoitteille personoitua data-analyttista lähtökohtaa. Tälle ratkaisulle esitellään uusi tietokonearkkitehtuuri, joka käyttää IoT-ratkaisun eri tasojen laskentaresursseja saavuttaak-

seen terveydenhuoltopalvelujen vaatimat korkea tasoinen saatavuuden ja laadun. Tämä mahdollistaa koneoppimisalgoritmien hierarkkisen osiointin näissä palveluissa, mahdollistaen samalla käyttötarkoitukseen sopeutuvan järjestelmän. Lisäksi esitellään personoituun tiedon yhdistämiseen ja mallintamiseen soveltuva tekniikka, joka käyttää IoT-järjestelmien monimuuttuja- ja pitkittäisaineistoja parantamaan terveydenhuolto- soveluksen käyttäjäkokemuksen laatua. Aluksi esitellään reaaliaikainen ja joustava puuttuvan tiedon päätöksentekotekniikka, joka sopeutuu erilaisiin aineistolähteisiin. Tämä tekniikka sovittaa erilaisia aineistolähteitä tarkkaan IoT-pohjaiseen päätöksentekoon ottamalla huomioon myös mahdolliset puuttuvat sensoriarvot. Lisäksi esitellään personoitu malli, joka havaitsee pitkittäisaineistossa tapahtuvan vaihtelun lisäksi yksittäiset tapahtumat. Tämä malli arvioi henkilöiden unenlaatua heiltä aiemmin kerätyn aineiston perusteella. Lopuksi tutkielma arvioi näiden tietokonearkkitehtuurien suorituskykyä pureutumalla kahteen erimerkkitapaukseen. Ensimmäinen esimerkki koostuu sydämen rytmihäiriön reaaliaikaista tunnistamista sydänpotilaista kerätystä sydänsähkökäyrästä (electrocardiography). Toisen esimerkin aineistona on äitiysterveyden seuranta-aineisto, jossa 20 äitiä seurattiin raskauden sekä synnytyksen jälkeen yhteensä seitsemän kuukauden ajan.

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Turku, December 2019

Iman Azimi

# List of original publications

This article-based thesis consists of the original publications listed below:

- Paper I **Iman Azimi**, Amir M. Rahmani, Pasi Liljeberg, and Hannu Tenhunen. Internet of Things for Remote Elderly Monitoring: A Study from User-Centered Perspective. *Journal of Ambient Intelligence and Humanized Computing*, 8(2):273-289, 2017
- Paper II Riitta Mieronkoski, **Iman Azimi**, Amir M. Rahmani, Riku Aantaa, Virpi Terävä, Pasi Liljeberg, and Sanna Salanterä. The Internet of Things for basic nursing care—A scoping review. *International Journal of Nursing Studies*, 69:78-90, 2017
- Paper III **Iman Azimi**, Arman Anzanpour, Amir M. Rahmani, Tapio Pahikkala, Marco Levorato, Pasi Liljeberg, and Nikil Dutt. HiCH: Hierarchical Fog-Assisted Computing Architecture for Healthcare IoT. *ACM Transactions on Embedded Computing Systems*, 16(5s):174:1-174:20, 2017
- Paper IV **Iman Azimi**, Janne Takalo-Mattila, Arman Anzanpour, Amir M. Rahmani, Juha-Pekka Soininen, and Pasi Liljeberg. Empowering Healthcare IoT Systems with Hierarchical Edge-Based Deep Learning. In *IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE)*, 2018
- Paper V **Iman Azimi**, Tapio Pahikkala, Amir M. Rahmani, Hannakaisa Niela-Vilén, Anna Axelin, and Pasi Liljeberg. Missing data resilient decision-making for healthcare IoT through personalization: A case study on maternal health. *Future Generation Computing Systems*, 96:297-308, 2019
- Paper VI **Iman Azimi**, Olugbenga Oti, Sina Labbaf, Hannakaisa Niela-Vilén, Anna Axelin, Nikil Dutt, Pasi Liljeberg, and Amir M. Rahmani. Personalized Maternal Sleep Quality Assessment: An Objective IoT-based Longitudinal Study. *IEEE Access*, 7:93433-93447, 2019

The following peer-reviewed publications were published/submitted during the course of my doctoral studies. They are not included in this thesis, but closely related.

- P-VII Amir M. Rahmani, Tuan Nguyen Gia, Behailu Negash, Arman Anzanpour, **Iman Azimi**, Mingzhe Jiang, and Pasi Liljeberg. Exploiting smart e-Health gateways at the edge of healthcare Internet-of-Things: A fog computing approach. *Future Generation Computer Systems*, 78(2):641-658, 2018
- P-VIII Kirsi Grym, Hannakaisa Niela-Vilén, Eeva Ekholm, Lotta Hamari, **Iman Azimi**, Amir M. Rahmani, Pasi Liljeberg, Eliisa Lyttyniemi, and Anna Axelin. Feasibility of smart wristbands for continuous monitoring during pregnancy and one month after birth. *BMC Pregnancy and Childbirth*, 19(1):34, 2019
- P-IX Delaram Amiri, Arman Anzanpour, **Iman Azimi**, Marco Levorato, Pasi Liljeberg, Nikil Dutt, and Amir M. Rahmani. Context-Aware Sensing via Dynamic Programming for Edge-Assisted Wearable Systems. *ACM Transactions on Computing for Healthcare*, 2019
- P-X Maximilian Götzinger, Arman Anzanpour, **Iman Azimi**, Nima TaheriNejad, Amir M. Rahmani, Axel Jantsch, and Pasi Liljeberg. Confidence-Enhanced Early Warning Score Based on Fuzzy Logic. *ACM/Springer Mobile Networks and Applications*, 2019
- P-XI **Iman Azimi**, Arman Anzanpour, Amir M. Rahmani, Pasi Liljeberg, and Hannu Tenhunen. Self-aware Early Warning Score System for IoT-Based Personalized Healthcare. In *eHealth 360*, pages 49-55, 2017
- P-XII **Iman Azimi**, Arman Anzanpour, Amir M. Rahmani, Pasi Liljeberg, and Tapio Salakoski. Medical Warning System based on Internet of Things using Fog Computing. In *International Workshop on Big Data and Information Security (IWBIS)*, 2016
- P-XIII Arman Anzanpour, **Iman Azimi**, Maximilian Götzinger, Amir M. Rahmani, Nima TaheriNejad, Pasi Liljeberg, Axel Jantsch, and Nikil Dutt. Self-awareness in remote health monitoring systems using wearable electronics. In *Design, Automation & Test in Europe Conference & Exhibition (DATE)*, 2017
- P-XIV Behailu Negash, Tuan Nguyen Gia, Arman Anzanpour, **Iman Azimi**, Mingzhe Jiang, Tomi Westerlund, Amir M. Rahmani, Pasi Liljeberg, and Hannu Tenhunen. Leveraging Fog Computing for Healthcare IoT. In *Fog Computing in the Internet of Things*, pages 145-169, 2017



- P-XV Delaram Amiri, Arman Anzanpour, **Iman Azimi**, Amir M. Rahmani, Pasi Liljeberg, Nikil Dutt, and Marco Levorato. Optimizing energy in wearable devices using fog computing. In *Fog Computing: Theory and Practice*, 2019
- P-XVI Maximilian Götzinger, Arman Anzanpour, **Iman Azimi**, Nima TaheriNejad, and Amir M. Rahmani. Enhancing the Self-Aware Early Warning Score System through Fuzzified Data Reliability Assessment. In *Wireless Mobile Communication and Healthcare*, pages 3-11, 2018
- P-XVII Axel Jantsch, Arman Anzanpour, Hedyeh Kolerdi, **Iman Azimi**, Lydia Chaido Siafara, Amir M. Rahmani, Nima TaheriNejad, Pasi Liljeberg, and Nikil Dutt. Hierarchical dynamic goal management for IoT systems. In *IEEE International Symposium on Quality Electronic Design (ISQED)*, 2018
- P-XVIII Delaram Amiri, Arman Anzanpour, **Iman Azimi**, Marco Levorato, Amir M. Rahmani, Pasi Liljeberg, and Nikil Dutt. Edge-Assisted Sensor Control in Healthcare IoT. In *IEEE Global Communications Conference (GLOBECOM)*, 2018
- P-XIX Emad Kasaeyan Naeini, **Iman Azimi**, Amir M. Rahmani, Pasi Liljeberg, and Nikil Dutt. A Real-time PPG Quality Assessment Approach for Healthcare Internet-of-Things. In *10th International Conference on Ambient Systems, Networks and Technologies (ANT)*, 2019
- P-XX Olugbenga Oti, **Iman Azimi**, Arman Anzanpour, Amir M. Rahmani, Anna Axelin, and Pasi Liljeberg. IoT-Based Healthcare System for Real-Time Maternal Stress Monitoring. In *IEEE/ACM International Conference on Connected Health: Applications, Systems and Engineering Technologies (CHASE)*, 2018
- P-XXI Sina Shahosseini, **Iman Azimi**, Arman Anzanpour, Axel Jantsch, Pasi Liljeberg, Nikil Dutt, and Amir M. Rahmani. Dynamic Computation Migration at the Edge: Is There an Optimal Choice? In *ACM Great Lakes Symposium on VLSI (GLSVLSI)*, 2019
- P-XXII Mohammad R. Nakhkash, Tuan Nguyen Gia, **Iman Azimi**, Arman Anzanpour, Amir M. Rahmani, and Pasi Liljeberg. Analysis of Performance and Energy Consumption of Wearable Devices and Mobile Gateways in IoT Applications. In *International Conference on Omni-layer Intelligent systems (COINS)*, 2019
- P-XXIII Arman Anzanpour, Delaram Amiri, **Iman Azimi**, Amir M. Rahmani, Marco Levorato, Pasi Liljeberg, and Nikil Dutt. Edge-Assisted Control for Healthcare Internet-of-Things: A Case Study on PPG-based Early

Warning Score. *ACM Transactions on Internet of Things* (submitted – minor revision), 2019

P-XXIV Johanna Saarikko, Hannakaisa Niela-Vilén, Eeva Ekholm, Lotta Hamari, **Iman Azimi**, Pasi Liljeberg, Amir M Rahmani, Eliisa Lyytyniemi, and Anna Axelin. Continuous 7-month IoT-based Health Monitoring of Pregnant and Postpartum Women—Observational Pilot Study. *JMIR mHealth and uHealth* (under review), 2019

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# List of Abbreviations

**BAN** Body Area Network.

**C-index** Concordance index.

**CNN** Convolutional Neural Network.

**ECG** Electrocardiography.

**eHealth** Electronic Health.

**EWS** Early Warning Score.

**ICT** Information and Communication Technology.

**IMU** Inertial Measurement Unit.

**IoT** Internet of Things.

**KL divergence** Kullback–Leibler divergence.

**KNN** K-Nearest-Neighbor.

**MAPE-K** Monitor-Analyze-Plan-Execute over a shared Knowledge.

**MAR** Missing At Random.

**MCAR** Missing Completely At Random.

**mHealth** Mobile Health.

**MLE** Maximum Likelihood Estimation.

**NMAR** Not Missing At Random.

**ODA** Observe Decide Act.

**PPG** Photoplethysmography.

**PSG** Polysomnography.

**QoE** Quality of Experience.

**RFID** Radio Frequency Identification.

**RMSE** Root Mean Square Error.

**RNN** Replicator Neural Networks.

**SVM** Support Vector Machine.

**WHO** World Health Organization.



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**II Original Publications** **103**



Part I  
Synopsis



# Chapter 1

## Introduction

Digital health and welfare services are transforming healthcare delivery and outcomes [130, 144]. Starting from the 20th century, telemedicine and telehealth have gained attention for remote delivery of healthcare services, reducing the distance barriers between patients and clinical teams [26, 207]. Telemedicine and telehealth consist of a broad range of applications including telephone helplines, sharing bio-signals and medical images over a network, and transmission of health records from medical centers to remote patients, just to mention a few. Electronic Health (eHealth) and Mobile Health (mHealth) were introduced in the early 2000s, exploiting Information and Communication Technology (ICT) such as mobile phones and the Internet to support healthy lifestyles, to improve quality of healthcare, and to mitigate healthcare costs [26, 69, 151]. These health services encompass patient monitoring, disease surveillance, and remote care supports.

In recent years, technological advancements in different fields of ICT have been revolutionizing human lifestyles [56, 115, 223]. First, due to the worldwide expansion of Internet-based services and mobile devices, the usage and demand for such services have dramatically increased across the world. Global mobile phone subscriptions rose from 2.2 billion in 2005 to 7 billion in 2015 [227]. Second, the Internet of Things (IoT) as an advanced network of objects is rapidly expanding in different sectors, where connected devices share their information to provide more efficient services [20, 95]. Cisco has estimated that by 2030 there will be 500 billion connected devices, each of which can perform data collection, interconnect with other devices, and actuate on its environment [52].

Moreover, the quality and capability of ICT-based services are being enhanced by sensing, communication, and computing infrastructures that are becoming more advanced and intelligent [193, 76]. For example, wireless sensor devices and embedded systems are being developed to be more energy-efficient, lightweight, and miniaturized; Internet connections are be-

coming more accessible and ubiquitous; and cloud computing machines are being equipped with higher computational capacity.

This synergy between technologies (e.g., IoT) and healthcare is opening new avenues in eHealth and mHealth. Ubiquitous health monitoring is a new healthcare paradigm in this regard, by which remote monitoring of patients can be carried out anytime and anywhere [215, 182, 115]. Such a holistic solution presents new opportunities to achieve a better quality of care, allowing reactive and proactive care for patients as well as empowering health providers to offer more accurate and cost-efficient services. However, this subject is still at an infancy stage and necessitates more research and development.

## 1.1 Ubiquitous Health Monitoring

Ubiquitous health monitoring is a multidisciplinary paradigm that allows tracking of patients' health conditions outside of conventional clinical settings. It facilitates the delivery of healthcare solutions, providing treatment support, preventive care, and early intervention in patient's everyday routines. Such monitoring is in high demand for individuals who require more intensive support and frequent screening. The elderly are a target group of this monitoring, as they are more vulnerable to disabilities and diseases [229]. This issue is more significant in the future since the world's elderly population is expected to be doubled - from 900 million in 2015 to 2 billion in 2050 [228]. Another group includes pregnant women whose health and well-being can be improved via ubiquitous health monitoring. According to the World Health Organization (WHO) [230], more than 800 women die every day due to preventable pregnancy and childbirth problems. In addition, ubiquitous health monitoring systems can benefit at-risk patients (e.g., individuals suffering from cardiovascular diseases), enabling early detection as a key to alleviate disease outcomes [153].

Ubiquitous health monitoring demands 1) continuous data collection of user's condition and surrounding context, 2) data analytic approaches for decision making, and 3) data transmission to health providers. IoT technologies allow the provision of such remote health applications, offering continuous connectivity between local devices and remote computing machines over the Internet network. Within this health monitoring, the IoT-based system can be partitioned into three main tiers, as shown in Figure 1.1.

The *sensor network* encompasses a variety of wireless sensors by which the user's condition is continuously recorded. For example, Body Area Network (BAN) is a wireless network of portable and wearable electronics (e.g., smartphones and smartwatches) that continuously acquire physical activity and health parameters. Depending on the applications, the data can be des-



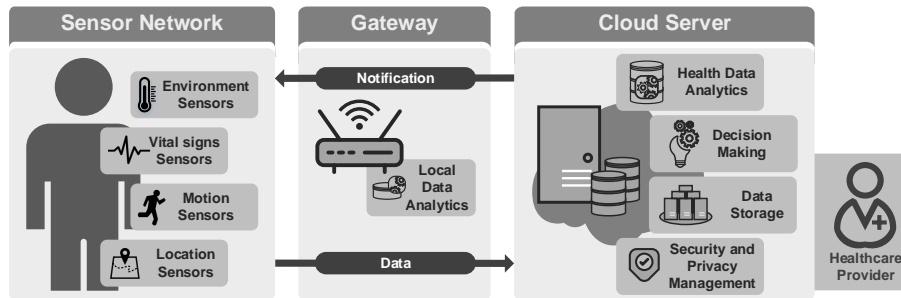


Figure 1.1: An IoT-based health monitoring system

ignated as big data because of the volume, velocity, and variety [48]. The *gateway* acts as an access point between the *sensor network* and the *cloud server*. It provides conventional services such as protocol conversion. In addition, alternative network infrastructures have been proposed to incorporate data analytic techniques into the gateway devices [185]. The *cloud server* provides data storage and high-level computing solutions to perform (big) data analytic techniques. It should be noted that data security and privacy management should be considered in the IoT systems, as the data might include sensitive personal information, and unauthorized access could cause critical problems [202, 4].

## 1.2 Research Problems

While IoT-based systems including BAN and data analytic methods are emerging to yield holistic solutions in the healthcare domain, new questions and challenges are being raised. The IoT-based systems operate over constrained shared resources. For example, wireless sensors are equipped with limited battery capacity; connectivity between gateway devices and servers might be degraded in different bandwidth use; and the computing algorithms might be affected by the limited computational and data storage capacity. Therefore, these systems need to overcome such obstacles and limitations, satisfying the requirements of their (health) applications. To this end, we can partition this problem into two complementary sub-problems which stress 1) *the health applications' characteristics and requirements* and 2) *the research and technical challenges in IoT-based system*.

The first important issue which needs to be addressed is to determine the tasks and requirements of IoT-based health applications from a user-centered perspective. IoT-based systems have thus far been exploited in many healthcare applications. However, there is still a demand for user-centered studies to identify the impact of these systems on user's health and

daily routine. Such studies should cover the requirements of the users, in both the in-home and in-hospital healthcare applications. Moreover, it is necessary to investigate the objectives of these systems and subsequently their limitations and challenges in real-world applications.

The second issue is to meet the challenges and requirements of IoT-based health systems. There is a large body of literature developing software and hardware solutions to improve IoT-based systems. However, many of the existing methods and software architectures are insufficient when these systems target health and well-being purposes. Due to the mission-critical nature of healthcare systems, a satisfactory Quality of Experience (QoE) is essential; and various quality attributes must be satisfied. For instance, an IoT-based system can provide an acceptable performance in a non-life-threatening smart city application (e.g., waste management), in which the unavailability of the service in the event of the loss of the Internet does no serious harm. However, such a system is unacceptable in a health deterioration detection application. Similarly, a real-time health data analytic approach must ensure high accuracy in disease classification while minimizing latency, as a rapid response is essential to mitigate health risks.

To satisfy adequate quality attributes and the user's needs, we need to design IoT-based health systems to act individually and specifically for each person. Such developments should be performed from two different aspects. 1) *system-driven aspect*: to improve the system's function and resource allocations. IoT-based systems need to provide an adaptive behavior to optimize the system's configuration according to the user's condition and context. 2) *data-driven aspect*: to enhance decision-making approaches within the IoT systems. IoT-based systems require data analytic approaches, including artificial intelligence and machine learning, to optimize the quality of healthcare and to support decision-making.

### 1.3 Research Objectives

This thesis investigates the two sub-problems, pursuing the following research objectives. Primarily, it is expected to delve deeply into the state-of-the-art IoT-based health monitoring systems. Such a survey should provide deep understanding of the role of IoT in existing home-based and hospital-based monitoring. In this regard, one research objective is defined to address the first sub-problem.

Moreover, it is expected to design, develop, implement, and evaluate innovative software architectures and data analytic approaches, meeting the objectives of IoT-based health applications. We believe such solutions can be obtained for ubiquitous health monitoring systems by exploiting IoT features such as multivariate data acquisition, context-awareness, and personalized

learning. Considering both the system-driven and data-driven aspects, two research objectives are defined in this thesis to holistically leverage data analytic approaches across the applications.

Correspondingly, the main research objectives of this thesis are as follows.

**Research Objective I:** Investigate and analyze the role of IoT-based systems in healthcare applications and to examine the existing trends, objectives, and challenges in these systems

**Research Objective II:** Design and implement a personalized IoT-based computing architecture, satisfying high-levels of quality attributes in real-time health monitoring systems

**Research Objective III:** Design and implement intelligent data processing and modeling techniques tailoring longitudinal and multivariate data in IoT-based systems to enable personalized decision-making in healthcare applications

## 1.4 Contributions

This thesis addresses the aforementioned research problems and subsequently fulfills the three research objectives. In summary, the contributions of this thesis are manifold:

- The state-of-the-art IoT systems exploited in home-based healthcare applications are investigated, focusing on the elderly who require more attention and care. In this regard, the existing literature is analyzed and categorized from a user-centered perspective – considering the requirements of the elderly. Moreover, the challenges and objectives of this research are evaluated to pave the way for designing more effective IoT-based systems and data analytic approaches in home-based monitoring.
- The literature is examined and analyzed to assimilate the role of IoT-enabled systems in hospital-based monitoring applications. The existing works are investigated and categorized into different domains –considering the needs of hospitalized patients, nurses, and health providers. The objectives are also presented to indicate how IoT-based systems and data analytic approaches can be tailored to overcome challenges and problems in hospitals and medical centers.
- A hierarchical computing architecture is introduced, enabling a personalized data analytic in IoT-based health monitoring systems. The

architecture allows the hierarchical partitioning of machine learning algorithms in IoT-based systems. It also enables a closed-loop management technique to automatically set the system's configurations with respect to the user's condition. The efficiency and functionality of the architecture are evaluated, in comparison with a baseline IoT architecture. In this regard, two case studies are exploited, focusing on real-time abnormality detection and arrhythmias detection applications used for patients suffering from cardiovascular diseases. The case studies are tested leveraging a Support Vector Machine (SVM) as a linear method and a Convolutional Neural Network (CNN) as a non-linear method.

- A real-time personalized health data fusion approach is proposed to deliver continuous health decision making despite missing values in data collection. The proposed approach tailors context information extracted from heterogeneous data resources to perform the missing data imputation. It also includes a personalized pooling to minimize the bias of the estimates. The approach is utilized for a real human subject trial on maternal health. The efficiency and functionality of the approach are evaluated in terms of the accuracy of the health decisions, in comparison to the existing missing data analysis methods.
- A semi-supervised machine learning approach is presented for long-term health monitoring, focusing on maternal sleep adaptations. The proposed approach creates a personalized sleep model for each user and utilizes the model to provide an explicit representation of sleep quality during pregnancy and postpartum in a comprehensive and personalized way. The approach is utilized for a real human subject trial on maternal health. The results show that sleep duration and sleep efficiency are deteriorated in pregnancy and notably in postpartum. The approach is compared with a baseline method to indicate how the proposed approach enables individualized and effective care during sleep monitoring.

## 1.5 Thesis Organization

This thesis is a collection of six original publications, five of which were published in international peer-reviewed journals and one of which was published in international conference proceedings. This article-based thesis is organized into two major parts, Part I: Synopsis and Part II: Original Publications.

Part I, Chapters 1-8, presents a summary of the research. The background of the thesis is outlined in Chapter 2. Chapter 3 includes state-of-

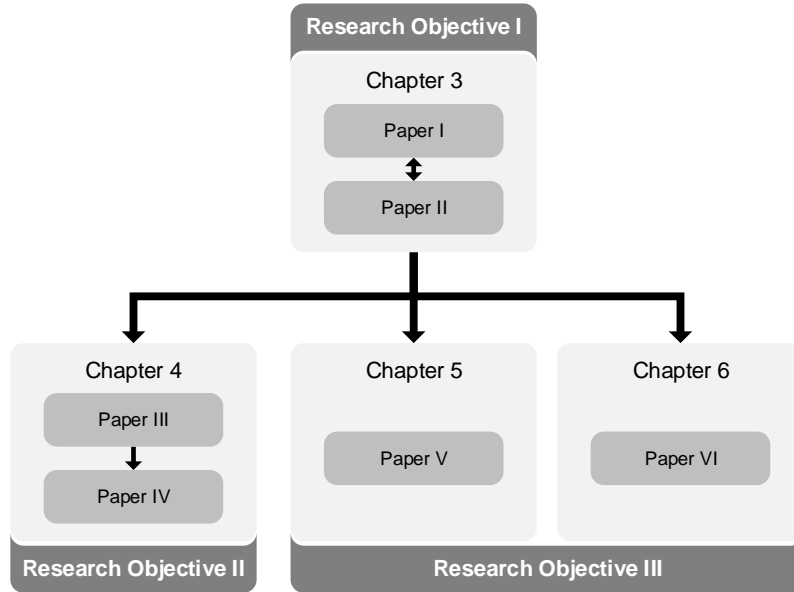


Figure 1.2: Organization of the papers, chapters, and research objectives in this thesis.

the-art IoT-based healthcare applications. Chapter 4 describes an IoT-based software architecture featuring an adaptive behavior with respect to the user’s data. Chapter 5 introduces a personalized data fusion algorithm to improve decision-making in IoT-based health monitoring systems, leveraging IoT-enabled multi-modal data collection techniques. Chapter 6 proposes a personalized model designed for objective longitudinal studies, extracting events and changes in user’s data. Conclusion and future work of the thesis are presented in Chapter 7. Finally, Chapter 8 presents a summarized overview of the original publications and the author’s contributions.

Part II consists of the six original publications. The attached articles support the aspects presented in Part I. In this regard, Paper I and Paper II are in accord with the contents presented in Chapter 3. They cover Research Objective I in this thesis, in which existing IoT-based health monitoring systems are examined. Paper III and Paper IV correspond to the contents of Chapter 4. They support Research Objective II, where an IoT-based hierarchical computing architecture is developed and assessed. Paper V covers the contents of Chapter 5; and finally, Paper VI corresponds to the contents presented in Chapter 6. Both the latter papers are in accordance with the Research Objective III in this thesis. An overview of the organization of the papers, chapters, and research objectives are shown in Figure 1.2.



## Chapter 2

# Preliminaries

This chapter briefly presents preliminaries of this thesis, including an overview of the IoT systems and fog computing paradigm. Then, it outlines two essential concepts of our case studies, bio-signals and maternal health.

### 2.1 Internet of Things

The Internet of Things (IoT) is a network of interrelated physical objects or “things” that acquire data, interact with each other, and communicate with remote servers. It tailors a variety of paradigms such as artificial intelligence, global communication infrastructures, and shared pools of data to deliver high quality and effective services. The concept of IoT was first introduced in 1999 by Kevin Ashton to supply chain management [17]. However, it was redefined later in different studies as the technology evolved in the past decades [95, 138, 20]. Due to the advancements in wearable electronics, data analytics, and wireless communication, the use of IoT is rapidly growing in many fields. The major strength of IoT is its impact on improving several aspects of everyday life, particularly health and well-being. For instance, smart hospitals could provide advanced care management services by continuously measuring and analyzing patients and personnel information [43].

Conventionally, the functions of IoT systems are divided into three main parts: data collection, data transmission across the Internet, and data analysis. In this regard, the architecture of such systems also can be partitioned into three layers [3] (see Figure 2.1). The perception layer includes smart devices equipped with sensing and communication capabilities. These devices with unique identities are located close to the monitored entities (e.g., individuals and objects) and contribute to collecting data from the entities and their environments. The data are shared with higher layers via wireless communication technologies such as Bluetooth, Wi-Fi, and ZigBee [138]. The gateway layer consists of multiple gateway devices that provide con-

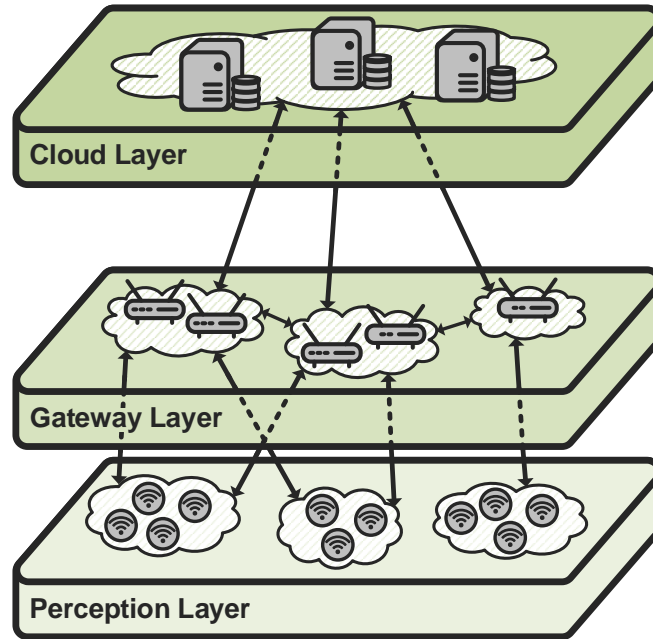


Figure 2.1: A generic 3-layer IoT architecture

tinuous connectivity between the perception layer and the cloud layer (i.e., the Internet). Each gateway device receives data from a sensor network, fulfills protocol conversion, and communicates with other local and remote devices. In addition, fog computing, a new concept of extending cloud computing to the edge of the network, is proposed to drive lightweight local data analytic applications at the gateway devices [33, 184]. The cloud layer contains remote servers enabled by powerful computational resources. As the back-end system, the cloud servers allow broadcasting, heterogeneous data analytic approaches, and data storage [205]. The cloud layer also offers data visualization services to the users through graphical user interfaces.

## 2.2 Fog Computing

Fog computing is a decentralized computing infrastructure, providing computing, communication, and storage facilities at the edge of the network [33]. As aforementioned, gateway devices are traditionally responsible for guaranteeing reliable connectivity and supporting wireless protocols. In IoT systems, fog computing brings an extended cloud computing paradigm to the gateway layer (i.e., vicinity of the sensor network). This concept expands the role of gateway devices, where several lightweight data processing techniques can be enabled locally. These techniques include data filtering,



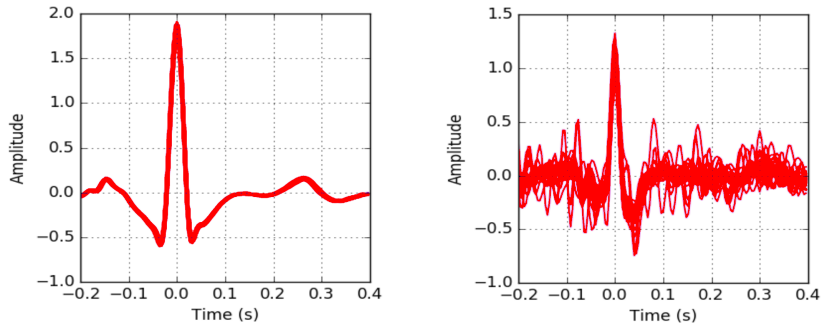
data integration, data compression, and local decision-making [185].

Fog computing serves as an intermediary between sensors and cloud servers to address various issues in IoT systems [51]. Some of the benefits are listed as follows. 1) *Latency reduction*: lightweight data processing (e.g., a rule-based decision making method) is fully positioned at the fog layer. Therefore, there is no need to send data to the cloud and await a response. This local processing could improve the response time of the system. 2) *Bandwidth utilization reduction*: data abstraction techniques can be performed in the gateway devices. Hence, instead of sending raw data, a simplified version of the data is sent to the cloud server. In addition, data compression methods can reduce the size of data transmitted over a network. 3) *Security and privacy enhancement*: IoT systems demand data security and privacy both in data transmission over a network and data storage in the cloud [202]. Outsourcing data processing techniques to the local gateway devices could reduce the risk of data breach [185]. 4) *Resource management and reconfigurability*: management techniques can be performed at the fog layer to analyze collected data and reconfigure the system's parameters accordingly. This could improve the energy efficiency of the IoT system [14, 8, 10].

## 2.3 Bio-signals

Bio-signals refers to bio-electrical signals that can be continuously recorded from an individual. Such signals can be exploited to extract various vital signs and subsequently determine the health status of a patient. Some of the conventional techniques to collect these bio-signals are Electrocardiography (ECG), Photoplethysmography (PPG), Electroencephalography (EEG), Electrooculography (EOG), and Galvanic skin response (GSR) [222, 186]. In this section, we briefly outline the ECG and PPG techniques as utilized in our case studies.

The ECG technique captures the electrical activity of the heart, indicating the depolarization and repolarization of cardiac muscles. The recorded signal represents cardiac cycles (i.e., heartbeats) and functioning of the heart [222, 88, 59]. It is the gold standard for measuring different health parameters such as heart rate and heart rate variability. Figure 2.2a illustrates sixty cardiac cycles of a one-minute ECG sample, in which the cycles are aligned to their peaks (i.e., R peaks). As this sample was collected from a healthy person, the cycles are almost identical. Moreover, ECG signals can be leveraged to detect various cardiovascular diseases including arrhythmias. Such diseases distort the shape of cardiac cycles or cause irregular heart rhythms. Sixty-seven cardiac cycles of a one-minute ECG sample with an arrhythmia is shown in Figure 2.2b, where the cardiac cycles are aligned with their



(a) Cardiac cycles of a one-minute normal ECG signal (b) Cardiac cycles of a one-minute ECG signal with an arrhythmia

Figure 2.2: Cardiac cycles obtained from two ECG samples

peaks. As indicated, the cycles are highly dissimilar in this ECG sample.

The PPG is a technique that records blood volumetric variations in the microvascular bed of tissues [7]. The PPG technique consists of two major components: 1) one or two light source(s) (e.g., an LED) to expose light to the skin surface and 2) one light sensor to capture the light reflected from the skin [213]. The signal, which is the reflected light, is associated with heartbeat and respiration oscillations. The PPG components are conventionally placed on the fingertip and are utilized to extract various vital signs such as heart rate, respiration rate, and peripheral oxygen saturation ( $SpO_2$ ).

The ECG and PPG techniques can play key roles in IoT-based health monitoring systems, as they are simple, non-invasive, and easy-to-use in everyday settings. For the data collection of both techniques, several wearable sensors have been proposed thus far. Smart chest straps and Holter monitors have been designed to continuously collect ECG signals [35, 93]. These sensors are mostly placed on the user's chest. Similarly, the PPG technique has been broadly utilized in several commercial and clinical wearable devices such as pulse oximeter, smartwatches, and smart rings [147, 9, 126]. For the data analysis, IoT systems tailor various signal processing and machine learning algorithms to continuously track user's health status and subsequently the early-detection of diseases (e.g., arrhythmias) and health deterioration [59, 213]. Depending on the application's and system's needs, such detection algorithms can be carried out in the local devices or remote servers.

## 2.4 Maternal Health

A woman's body undergoes radical physical, hormonal, and physiological changes during pregnancy. These changes prepare the maternal body for the accommodation of the fetus and for the forthcoming childbirth [111, 218]. However, such changes might lead to adverse pregnancy outcomes (e.g., preterm birth and gestational diabetes) in pregnant women with high-risk conditions such as preeclampsia and obesity [234, 62]. Even in healthy mothers, pregnancy changes might contribute to unmasking pre-existing diseases [190]. Therefore, maternal health –the health of the mother during pregnancy, during labor, and in the postpartum period– is essential and should be considered carefully. Traditionally, maternal care services are merely performed in healthcare centers during certain appointments in the pregnancy. However, this is considered insufficient, as the pregnancy progress cannot be monitored constantly.

IoT-based systems can contribute in this regard, enabling continuous maternal health monitoring during pregnancy and postpartum [176, 94, 129]. Such longitudinal monitoring allows continuous monitoring of multiple health and pregnancy-related parameters including vital signs, physical activity levels, and sleep quality. Therefore, abnormalities and complications in pregnancy can be identified as soon as possible and be treated accordingly. Moreover, these monitoring systems maximize the availability of maternal health, where pregnant women can also be involved in their own everyday care processes.



## Chapter 3

# IoT-enabled Healthcare

IoT-based health monitoring systems are transforming modern healthcare, enabling smart health applications within hospitals and medical centers and also outside of conventional clinical settings. Thus far, tremendous research work has been devoted to tackle various health problems, leveraging ICT- and IoT-based systems. This chapter presents the existing work, trends, and challenges in IoT-based health monitoring systems propelled by in-home and in-hospital applications. In this regard, the in-home applications are categorized from a user-centered perspective, focusing on the elderly as vulnerable subjects whose population is increasingly growing. On the other hand, the in-hospital applications are partitioned according to the demands of both patients and health providers.

### 3.1 Home-based Monitoring

IoT has already had profound impacts on several home-based monitoring domains. The existing applications in the literature can be categorized differently depending on the type of sensor network (e.g., BAN), the scale of the system, and the user's requirements. This thesis divides the existing works into different subgroups based on their proposed services targeting aspects of users. The systematic search process is conducted through the applications proposed to the elderly who require intensive supports 24/7. Figure 3.1 indicates a multi-layer IoT system for home-based elderly monitoring. It should be noted that this classification can be applied to other groups of people who require prevention and early-intervention services.

#### 3.1.1 Health parameters

Health parameters monitoring is one of the major sectors in remote health services, where acute and chronic diseases are screened for early-detection of possible health deterioration [115]. Such monitoring is highly in demand for

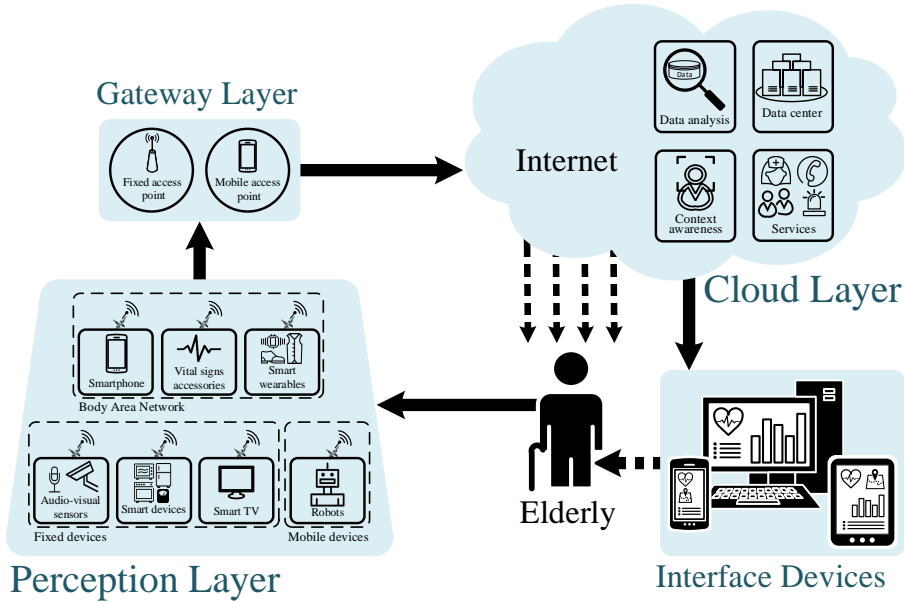


Figure 3.1: An IoT-based system for home-based elderly monitoring

the elderly due to the increase of frailty, risk factors and health problems in old ages. This will become more important in the near future as a decrease in the potential supportive ratio (i.e.,  $\frac{\text{Population with age } 25-64}{\text{Population with age } +65}$ ) is expected [224].

Monitoring systems have been proposed to determine user’s medical status, collecting various vital signs according to different guidelines. For example, a remote health monitoring system was proposed to extend a hospital-based scoring system entitled the Early Warning Score (EWS) [162, 5, 131] for home settings. The system was designed to collect heart rate, breathing rate, body temperature, blood pressure, and blood oxygen saturation to detect possible serious medical states in daily routines [23, 14]. Similarly, in elderly monitoring, different systems have been developed. For example, an IoT-based system enabled by an Android platform was proposed to remotely collect medical parameters including blood pressure, glucose, and weight [189]. In this system, the data was sent to a cloud server to perform data processing algorithms as well as sharing the data and feedback with health providers and caregivers through interface devices [183]. Moreover, a system including wearable textiles [71] and a companion robot was introduced in MOBISERV [168] for elderly health monitoring, collecting various health parameters.

Other attempts have been done to remotely monitor daily routines of senior adults. In this regard, physical activity and posture tracking have been implemented, leveraging recognition models, omnidirectional vision

sensors [232], and wearable sensors such as smart hats and smart shoes [124, 46]. Similarly, daily activities including the act of eating and sleeping of elderly people have been monitored via an IoT-based system equipped with a textile capacitive neckband [50]. In addition, elderly fitness tracking has been introduced to provide a real-time service for physical activity monitoring along with a personalized fitness program empowered with the feedback of the sensors [40].

To increase the feasibility of the monitoring, some proposed systems were restricted to conventional and user-friendly setups. For instance, a remote health monitoring system equipped with wearable electronics was proposed, where the individuals could interact with the system via a digital TV [209]. Similarly, a TV-based system was introduced to offer various services to deliver health applications as well as social communication services [145, 105].

### 3.1.2 Nutrition

Nutrition assessment systems evaluate the nutritional status of users, exploiting subjective and objective data collection. Such systems become essential for patient's at-risk (particularly elderly), as malnutrition (e.g., under/over nutrition) has a negative impact on their health quality and make them susceptible to various diseases [225]. Different IoT-based nutrition monitoring systems have been introduced, supporting food-related monitoring.

There have been both software and hardware developments in this regard. For example, a mobile application was designed to enable subjective data collection and objective data collection by connecting smartphones to other devices such as weighing scales [64]. In contrast, a wearable device equipped with a visual sensor was introduced in another work to monitor daily diet. The proposed device could estimate food portions and calorie intake, leveraging prior information about food shapes [211].

Moreover, IoT-based monitoring systems were proposed tailoring wireless devices (e.g., scale), personal robotic systems, and cloud services to extract information from daily activities (e.g., self-feeding). These systems could provide weight and diet monitoring as well as shopping and cooking assistance [135, 194, 114].

### 3.1.3 Safety

Safety and security monitoring is another major category in home-based applications, where individuals receive interactive assistant and support services continuously. Such services provide independent living for users suffering from visual and physical impairments. With this intention, different

IoT-based monitoring systems were proposed targeting different aspects.

Fall detection systems have been introduced to provide early intervention for people with a high risk of falling, as a rapid response is instrumental in preventing irreparable damages and even death. Conventionally, the developments in fall detection systems are divided into two categories. First, wearable electronics and smartphones have been employed to perform continuous fall detection, where 3D accelerometer, gyroscope, and magnetometer were used to detect sudden changes in user's positions and orientations [73, 178, 122]. Second, context-aware systems have been developed, leveraging visual sensors (e.g., camera and Kinect) for fall detection [30, 180, 179]. Compared to the wearable sensors, context-aware systems increase the feasibility of the monitoring, removing the need for using sensors all the time. On the other hand, context-aware systems are limited to fixed-position sensors, so fall detection service is restricted to certain locations.

Behavior changes of users have been monitored using IoT-based systems, investigating unusual activities such as depression and mobility decrease. Such systems were proposed to collect home activity and location data via wearable sensors and cameras. They could determine abnormal and unexpected behavior comparing the data with prior models and subsequently send feedback to caregivers [29, 192]. In addition, IoT-based monitoring systems included environmental accident detection. Such systems were designed to collect environmental data to early-detect accidents such as gas leakage, fire, and carbon monoxide presence [29, 60].

### 3.1.4 Social Network

Home care and communication applications support and promote social life for users who require more interactions with other people. Developments in these applications included both mobile applications and devices. A simplified interface device empowered by multilingual speech interactions was proposed for people with physical impairments or computer illiteracy [37, 156]. Moreover, a virtual assistive companion was developed to collect user's behavior and to respond properly [217]. The platform offered to simulate human interactions, targeting (senior) adults living alone. It also provided notifications and reminders for taking medicine, doing exercise, and interacting with their family. In other attempts, interactive assistant systems have been introduced to allow vocal-driven interaction with users and social networking [6, 85]. These systems also offered public services such as shopping assistance and Meals on Wheels.



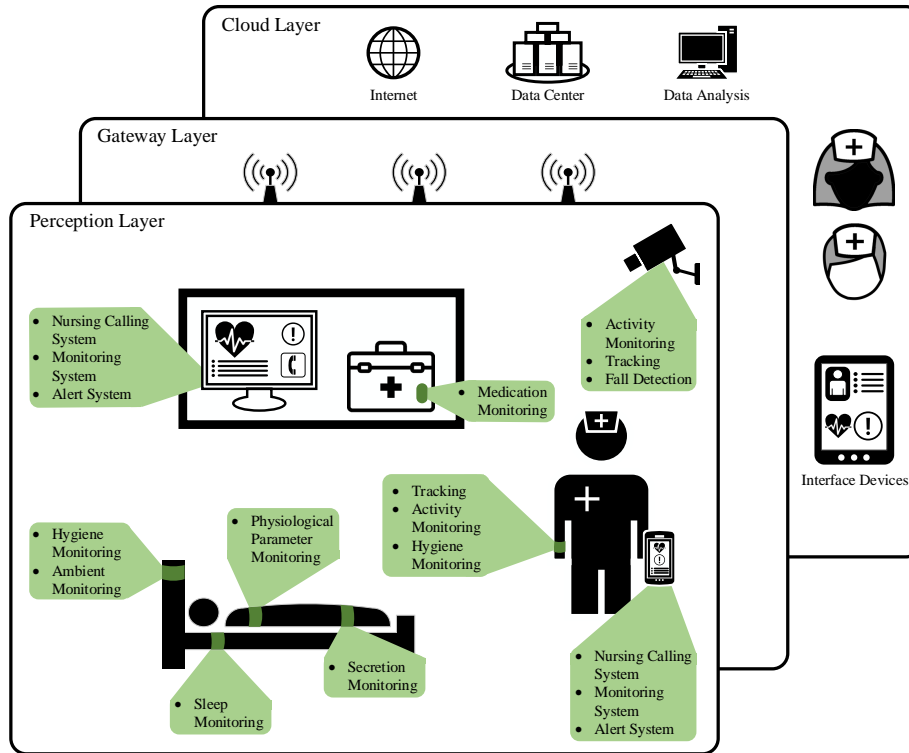


Figure 3.2: An IoT-based system for hospital-based monitoring

## 3.2 Hospital-based Monitoring

IoT-based systems, including connected objects and Internet-based services, can be utilized to meet a variety of challenges in hospitals. First, they can provide real-time monitoring to enable holistic solutions, minimize human errors, and generally improve the quality of care. Second, these systems enable autonomous services, tackling work environment issues. In this regard, they can carry out improvements in workload reduction and hospital management systems. A 3-layer IoT system for hospital-based monitoring is shown in Figure 3.2. In the following, existing IoT-based systems proposed for hospital applications are outlined.

### 3.2.1 Health Parameters

Similar to the home-based solutions, health monitoring can be performed in hospitals using wireless BAN connected to a network. The BAN can include a variety of wearable sensors, recording various health-related parameters. For example, a noninvasive cuffless band has been proposed to collect ECG, respiration rate, and blood pressure in real-time [74]. Wireless ring sensors

were also developed to record heart rate, heart rate variability, and physical activity data [109, 126]. Moreover, a versatile system was introduced to detect heart rate, respiration waveform, and skin temperature via a wearable device [61]. In other studies, continuous respiration monitoring was proposed where the respiration rate was extracted from chest movements or airflow humidity changes in patient’s nasal prongs or breathing masks [237, 11, 96]. In addition to the wearables, contactless sensors were introduced for vital sign monitoring. One instance is the use of a smart pad placed under the hospital’s beds, by which respiration rate is extracted from the capacitive coupling variation of the pad’s traces [99].

Additionally, wireless systems were developed for neonatal monitoring, where vital signs were collected to detect possible health deterioration. For example, a system was designed to continuously record respiratory signals collected from infants’ chest movements and to send notifications to nurses in case of apnea detection [110]. Moreover, a sensor network was designed for an incubator in a neonatal intensive care unit to acquire infants’ vital signs as well as environmental parameters [166]. The sensor network was connected to a gateway device for data analysis as well as sharing the data with the hospital information system.

### **3.2.2 Medication**

Medication monitoring and pharmaceutical intelligent information systems can be carried out in hospitals using IoT technologies. Such systems provide an intelligent drug delivery, reducing adverse drug reactions. In this regard, Radio Frequency Identification (RFID) techniques were leveraged to track medicines from prescriptions to the patients [118]. This information was integrated with the patient’s profile to automatically determine possible drug reactions and to send notifications to the nurses. In addition, such medication monitoring systems enabled by RFID were utilized for hospital’s supply chain management systems, enabling medication control from purchase to distribution [108, 133].

### **3.2.3 Sleep**

Sleep is an important indicator of the health and well-being of a person. IoT-based systems are exploited to track and evaluate the quality and quantity of sleep in both home-based and hospital-based applications. Sleep monitoring and assessment have been performed for hospitalized patients, utilizing wireless connected devices. Different wearable systems including a neck-cuff tool and Polysomnography (PSG) and actigraphy techniques were developed for patient’s sleep quality evaluation and sleep apnea early-diagnosis [191, 31, 65]. The systems could analyze collected acceleration data and ex-

tract information about the patient’s sleep patterns in hospitals. Moreover, motion-sensing mattresses were also developed to continuously monitor and analyze patient’s sleep postures, sleep movements, and pressure distribution [143, 236]. In contrast to the hospital-based applications, home-based sleep monitoring applications were mostly bounded to subjective measurements including self-report questionnaires. More details about the home-based sleep monitoring applications can be found in Chapter 6.

### **3.2.4 Tracking**

Smart hospitals have been introduced in different studies to remotely track patients, personnel, and devices in hospitals [42, 43]. Such tracking systems were proposed to improve emergency situation management, leveraging models and RFID techniques [41]. In addition, such a connected network could improve nursing calling systems. An IoT-enabled system was proposed in this regard, enabling the patients to make a nurse call request through a platform [81]. The location data of patients and nurses could improve the calling system by minimizing the time between sending the request and the nurse arrival [123, 199].

### **3.2.5 Hygiene**

Hand hygiene is an important practice to alleviate infection transmission in hospitals. IoT-enabled systems have been introduced to improve hospital hygiene and infection control. Real-time hand hygiene monitoring systems were developed to monitor hand hygiene of hospital personnel using RFID and wrist-worn sensors [27, 158, 154, 82]. These systems could classify the hand hygiene movements and provide a notification if the hygiene was inadequate or missed. In addition, a hand hygiene system was proposed to remind and encourage health professionals via interface devices to practice hand antisepsis [16]. Moreover, secretion monitoring systems were proposed for hospitals enabled by wetness sensors placed in diapers. These systems remotely detected soiled diapers and sent notifications to the nurses accordingly [220, 79].

## **3.3 Objectives and Challenges in Healthcare IoT**

As discussed, IoT-based monitoring systems have been thus far deployed in a broad range of applications, enhancing the quality of care in clinical and everyday settings. These IoT-based systems should satisfy a set of requirements to deliver high quality attributes to the end-users. These requirements are determined according to the applications’ objectives. The

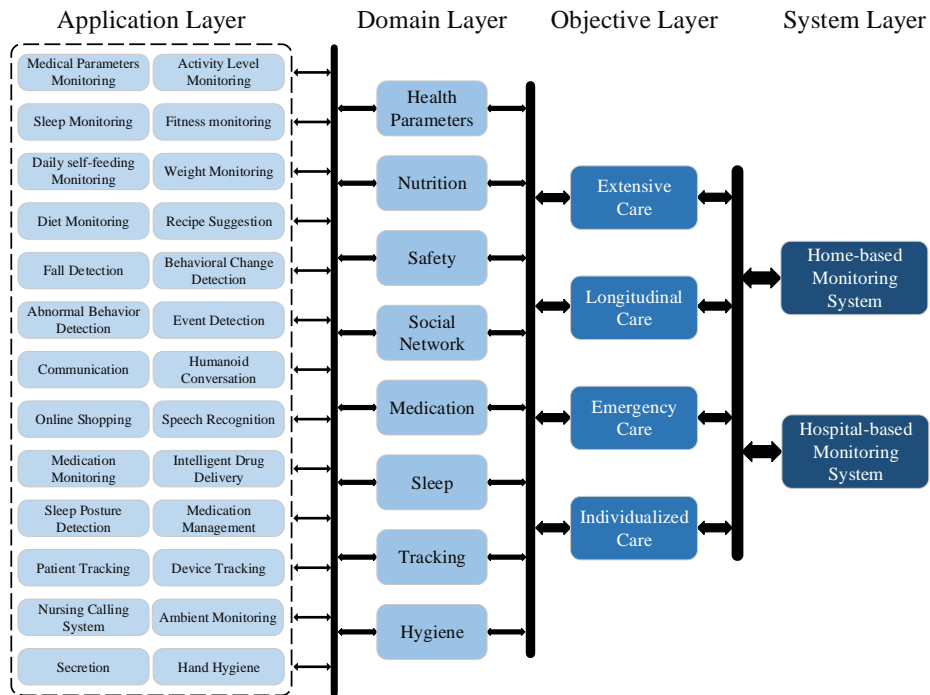


Figure 3.3: A hierarchical model for the IoT-enabled healthcare

objectives – which vary from one application to another – should be investigated for designing and developing IoT systems: from devices to data analytic approaches.

We address this issue by categorizing the existing applications into 4 parts according to their objectives. Figure 3.3 illustrates the hierarchy in these monitoring systems and the relation of the layers. The application layer is a subset of the domain layer. The objective layer covers the domain layer, and the system layer includes all the divisions and aspects. The application and domain layers include the existing works and sub-groups discussed in Section 3.1 and Section 3.2. The objective layer shows the objectives of IoT-enabled healthcare, and the system layer consists of the home-based and hospital-based monitoring systems. In the following, we briefly discuss the 4 objectives and some of their challenges.

### 3.3.1 Extensive Care

The scope of conventional health systems is mostly narrowed to a specific care or disease. In contrast, IoT-based monitoring systems provide extensive care and multipurpose applications where the user’s health and well-being are monitored comprehensively. In other words, IoT systems can integrate

applications of both home and hospital monitoring into one all-inclusive service, where the needs of the user (which is in the center of monitoring) are satisfied.

Such a system requires a heterogeneous data collection, so energy-efficient wireless BAN is needed which includes multiple lightweight wearable sensors. The scalability is the capability of managing a growing amount of load in the system. Such health monitoring should consider scalability, where the system needs to be updated, as user's needs might change during the monitoring [12, 163]. Moreover, data fusion tools are required to tailor different data resources (i.e., global knowledge) into the analysis and decision-making. In these systems, data fusion can be divided into three types: complementary, competitive, and cooperative [63, 66]. 1) Complementary: different parameters are collected to obtain a more complete parameter. For example, in the EWS method, different vital signs (including heart rate and breathing rate) are collected to detect health deterioration patients [5, 131]. 2) Competitive: one parameter is collected using different sensors to improve fault tolerance and accuracy. For instance, heart rate values are acquired from different wearable devices. 3) Cooperative: one parameter is recorded using different resources to derive new information. For example, multiple accelerometers are placed on the body (e.g., wrist and leg) of an individual for activity recognition [19].

### 3.3.2 Longitudinal Care

Longitudinal care is another objective in the IoT-based systems, by which the users are monitored for a long period of time. Such monitoring systems can be leveraged for diagnosis and treatment purposes, investigating the status of a disease over time. For example, chronic diseases and mental illnesses could be assessed via long-term care. In addition, these systems can be used for coaching and lifelogging purposes, to track trends, variations, and special events in the user's daily behavior and lifestyle [102, 117].

Energy efficiency is an important issue in these systems which use wearable sensors equipped with limited batteries [187]. Intelligent approaches are required to reduce sensing and transferring energy consumption of the sensor nodes. Such approaches should dynamically re-tune the system's configurations according to the conditions of the user and the system. For example, the data collection rate can be reduced if the vital signs are stable. However, the rate should be at its maximum when the medical state of the user is critical [14]. Such dynamic behavior can be obtained by using context-awareness and goal management methods performed in the fog or cloud paradigms [8, 9].

Moreover, the QoE should be investigated in IoT-based healthcare applications, as the users are the recipients. The QoE focuses on the service

experience and indicates how the service is delivered to the users. The requirements of the QoE are determined according to the applications. Different factors in the three layers of IoT systems might affect the QoE. Examples of such factors are the performance of the sensors (e.g., the accuracy of data collection), the delay of the network, and the interactivity of the service. The QoE should also be determined according to the end-users (e.g., patients and health providers) who use IoT-based health applications. For example, the usability and feasibility of the sensor nodes (e.g., being non-invasive, easy-to-use, and compact) can influence the QoE of the patients, particularly in long-term health monitoring [77, 78, 201].

In addition, data security, privacy, and data ownership play key roles in the long-term monitoring. The IoT-based systems should securely manage to collect, transmit, and store the data. First, access to the sensors (i.e., physical objects) should be limited, so the flaws are reduced. Second, the gateway devices need to manage data transmission securely. Security mechanisms (e.g., encryption algorithms) can be used in this regard. Third, the data should be protected in the cloud servers using different authentication and access control methods. It should be noted that these issues are not limited to longitudinal care and should also be considered for other healthcare services [4, 12, 233].

### 3.3.3 Emergency Care

Another objective of the IoT-based health monitoring is to enable emergency care, in which at-risk patients are monitored 24/7. IoT systems continuously collect health data, perform decision-making, and notify health providers and/or caregivers in case of emergencies. This procedure can provide early detection of health deterioration and subsequently early-intervention in medical emergencies. Such rapid responses are essential to fulfill effective treatments of acute diseases (e.g., heart attack and stroke) and accidents (e.g., a fall) [171].

There is a high risk of health deterioration in this monitoring. Therefore, to support these health applications, IoT-based systems should satisfy a high-level of availability. Unfortunately, traditional client-server cloud-based IoT systems are inappropriate for such applications. These systems rely on cloud servers for data analysis, so the application is interrupted when the cloud connectivity is unstable. In addition, these applications are latency-critical, so the systems' response time should be investigated. Response time of an IoT-based system is dependant on several variables in the system such as bandwidth, transmission channel reliability, and computation (e.g., decision making) time [198]. Furthermore, these systems demand high resilience to deliver an acceptable service despite the occurrence of faults [210].

### 3.3.4 Individualized Care

Individualized care is another objective in the IoT-based healthcare systems. Traditionally, diagnosis, treatments, and health decision-making are performed based on general assumptions and population data. In contrast, IoT-based systems can provide these health services with respect to the user's condition, where the decisions might differ from one person to another. These systems should extract personalized rules and models and then react to a health condition accordingly [210, 115, 231].

High learnability and adaptivity are essential quality attributes, as these systems need to learn continuously from the collected data. In this regard, these systems demand modeling, artificial intelligence, and machine learning algorithms to obtain data patterns over time and extract relations between different data features. Management techniques are also required to adaptively configure the IoT system according to the system's and user's conditions. These updates could include configurations of data collection, data transmission, and data analysis process.

In addition, intelligent techniques are required to investigate the reliability and confidence of data in IoT-based systems, indicating the degree of validity of the health application's results. This validation should be performed through personalization, where various sources of data – including user's condition, system's status, environmental data, and history data – are utilized. Self-awareness and context-awareness concepts can be exploited in this regard, incorporating such data sources into the validation of the results [92, 91, 107, 95].

## 3.4 Summary

This chapter introduced a review of the state-of-the-art IoT-enabled systems that are exploited in healthcare. The review was performed from two aspects: home-based and hospital-based applications. We investigated these studies and categorized them into different domains from a user-centered perspective. Home-based monitoring applications focused on the elderly who require more care and support, comparing to the population with age less than 65. Hospital-based monitoring applications were designed to address the needs of both patients in hospitals and health providers. We then analyzed the findings and presented the objectives of the IoT-based healthcare systems and discussed the challenges that should be satisfied in these systems.

The following chapters will attempt to tackle some of the challenges in IoT-based healthcare systems by developing personalized data analytic approaches. Chapter 4 will address availability and response time (i.e., latency) in real-time health monitoring systems, proposing a new software architec-

ture for IoT-based systems. Chapter 5 will propose a data fusion method to improve the system's resilience. Moreover, Chapter 6 will introduce a personalized decision-making approach to improve the accuracy of decisions and effective care in long-term health monitoring systems.

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Figures 3.1 and 3.2 were taken from Paper I and Paper II respectively.



## Chapter 4

# Computing Architecture for IoT-enabled Healthcare

As discussed in Chapter 3, IoT-based systems should provide adequate quality attributes according to the objectives and requirements of the applications. Such requirements are more difficult to meet when health monitoring applications are expected to continuously collect and analyze data and to correctly detect medical emergencies early enough. Therefore, high-levels of availability, reliability, and accuracy are demanded.

Conventionally, two IoT computing architectures have been proposed in the literature for such healthcare applications. First, cloud-based architectures were developed to collect data, transmit the data to the cloud servers, and perform data analytic approaches [34]. Using these architectures, IoT-based systems have been proposed that remotely monitor various health parameters [160, 208, 75, 89, 15, 23]. As the cloud servers can be equipped with powerful computational resources, these architectures are appropriate for non-safety applications, in which latency is not a critical factor, and high accuracy is demanded. Examples are smart city applications enabled by powerful machine learning algorithms. However, the function of the cloud-based architectures is highly dependent on the availability of the network, since they are unable to deliver services in the case of loss or degraded access to Internet connectivity. Therefore, these IoT architectures cannot satisfy IoT-based health monitoring applications.

Second, fully distributed fog-based architectures were proposed to collect data and perform local data processing at the edge of the network [33, 185]. In the literature, various studies have used these architectures to propose health monitoring systems [55, 43, 86, 14]. The fog-based architectures can provide local basic, and yet important, applications with high-levels of accessibility and reliability. However, the functionality is restricted to the limited processing power of gateway devices, so the IoT systems are unable to run

powerful machine learning approaches. Consequently, these conventional architectures are also insufficient for health monitoring applications.

This chapter proposes a new software architecture to satisfy system-driven quality attributes in an IoT-based health monitoring system. The proposed architecture leverages the features of both fog-based and cloud-based computing, allowing hierarchical partitioning and execution of machine learning in IoT-based systems. Moreover, it enables an autonomous closed-loop resource management technique, by which the system’s configurations are adaptively set according to the user’s condition.

In the following, first, a computing model is introduced, which is selected as the backbone of the architecture. Then, the computational units and management tasks are defined and mapped cross the 3-layer of IoT-based systems. Finally, the proposed architecture is evaluated, demonstrating a full system implementation for a case study on real-time arrhythmia detection in ECG signals.

## 4.1 Computing Model

Monitor-Analyze-Plan-Execute over a shared Knowledge (MAPE-K) is an existing computing model, enabling automated management for computational units and self-adaptive behavior in distributed systems. The computing model was first introduced by IBM [112, 125]. It provides a feedback loop including 4 different computing components, all of which have access to shared knowledge. The components are as follows. 1) *Monitor* is the closest component to the sensing tier, acquiring and aggregating data. 2) *Analyze* analyzes and models the data. 3) *Plan* constructs a procedure for the system according to the analysis. 4) *Execute* implements the procedure, providing necessary changes in the system.

The four computing components are utilized to enable the hierarchical IoT architecture. Moreover, we include another component entitled as *System Management* to the computing model to implement the closed-loop technique. The *System Management* is responsible for reconfiguring the system’s settings according to the feedback from the user’s condition. A view of the enhanced MAPE-K model with the computing components is shown

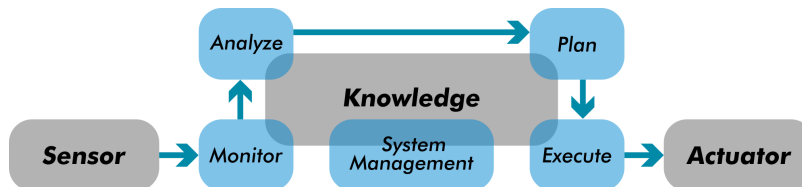


Figure 4.1: Enhanced MAPE-K computing model

in Figure 4.1.

## 4.2 Hierarchical Computing Architecture

The hierarchical computing architecture is proposed to leverage the benefits of both fog and cloud computing. The main idea of using MAPE-K in this architecture is to allocate 1) the heavy training process of a machine learning algorithm to the cloud server, and 2) the decision-making process to the gateway layer, outsourcing the trained inference to the edge of the network. The local decision-making allows resource management at the edge of the network, where the fog device is capable of reconfiguring sensing and transmission settings with respect to the user's condition. The proposed architecture enabled by this self-adaptive behavior (indicated by blue arrows) is shown in Figure 4.2. It includes the flow of observation, decision making, and action.

As illustrated in the figure, the MAPE-K computing components are mapped into the IoT system. The perception layer includes the *Monitor* component acting as a bridge between the sensors and the other computing units. The gateway layer consists of three components to perform local decision-making (*Plan*), to set the systems' behavior (*Execute*), and to tune the system configurations (*System Management*). Finally, the cloud layer includes the *Analyze* component which is responsible for training an inference (i.e., hypothesis function) from the user's data. The roles of these computing components in this architecture are outlined as follows.

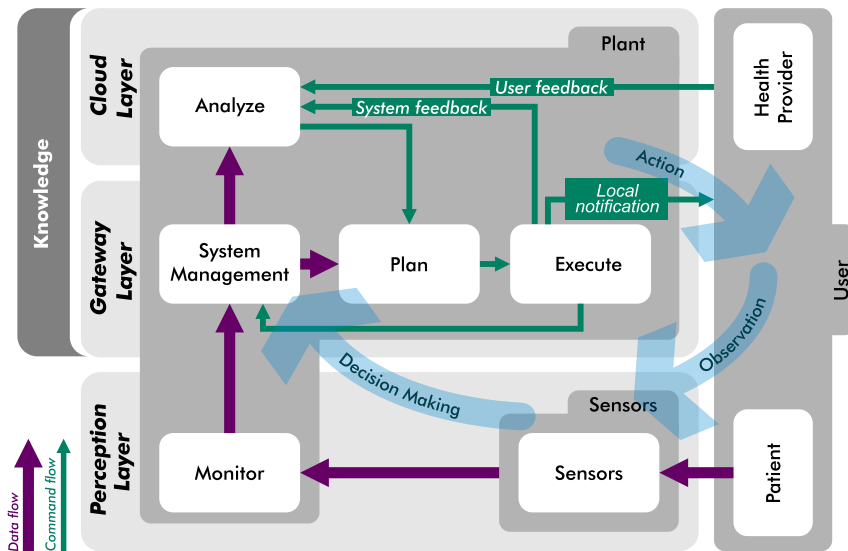


Figure 4.2: The proposed hierarchical computing architecture

### 4.2.1 Monitor

The *Monitor* is responsible for driving lightweight services at the sensor network and transmitting the data to the gateway layer. As indicated in Figure 4.3a, the component consists of 3 units. 1) An Analog-to-Digital Converter (ADC) converts analog signals acquired from the sensors into digital signals. 2) A MicroController Unit (MCU) performs data aggregation and pre-processing methods (e.g., noise filtering). 3) A transmitter unit sends the data to the *System Management* component.

### 4.2.2 Analyze

The *Analyze* component fulfills heavy data analytic techniques such as data modeling or training a classifier. Different machine learning algorithms can be fitted into this architecture. As illustrated in Figure 4.3b, the learning algorithm infers a hypothesis function using the training data which include the training samples and the corresponding labels. At the system's initial phase (i.e., design time), the training samples includes the medical history data (i.e., population data) and the labels obtained from users' feedback. The trained hypothesis function is stored at the *Final Hypothesis* unit to be sent to the *Plan* component, enabling decision-making at the gateway layer.

At run time, the streaming data are being received to re-train the hypothesis function (see Figure 4.3b). The data includes the sensor data received from the *System Management* component and the user/system feedback. The *Training Data* unit is responsible for the pre-processing algorithms (e.g., feature extraction). In this system, the hypothesis function is periodically re-trained. The update period (e.g., every day or every week) is selected according to the needs of the application and the types of the sensor data. Therefore, the classification becomes personalized during the monitoring. When the hypothesis function is updated, it is transmitted to the *Plan* component.

It should be noted that the selection of the learning algorithm depends on a variety of factors such as the nature of the data (i.e., signal), the type of health applications, and the output of the algorithm. Various linear and nonlinear algorithms such as a support vector machine and an artificial neural network can be used. However, the instance-based algorithms (e.g., K-Nearest Neighbor) are inapplicable, as the training dataset and the classifier cannot be separated in these algorithms.

### 4.2.3 Plan

The *Plan* component carries out local decision-making and sets the procedure of the system. The streaming data –coming from the *System Management* (i.e., sensor data)– are first processed (e.g., feature extraction) in the

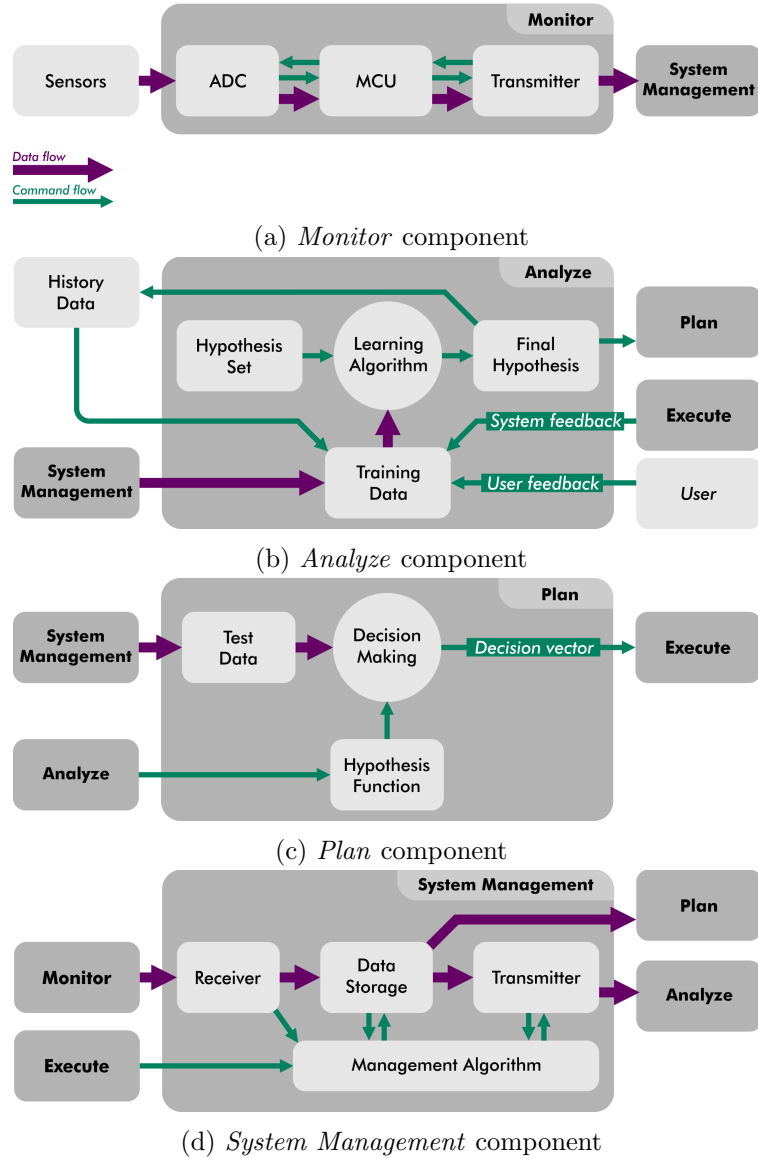


Figure 4.3: Major computing components of the proposed architecture

*Test Data* unit and are then classified using the hypothesis function (see Figure 4.3c). The output of the *Decision Making* is a decision vector indicating the user's current health status, which is a binary value (i.e., normal or abnormal) or a multi-class decision (i.e., types of diseases). The vector is sent to the *Execute* for the system's actuation.

At design time, the *Plan* utilizes the initial hypothesis function generated in the *Analyze* component using population data. However, as mentioned previously, the *Plan* is updated periodically at run time by receiving re-trained hypothesis functions from the *Analyze* component.

#### 4.2.4 Execute

The *Execute* is responsible for the system's actuation, sending feedback to the other units. First, it sends a notification to the users if an abnormality is detected. This process includes forwarding notifications to the patient and health providers. Second, the *Execute* updates the *System Management* component. Therefore, the system is able to re-tune its configurations according to the current status of the user. Finally, this computing component sends feedback (e.g., a report of the local decisions) to the *Analyze* component for the re-training process of the classifier.

#### 4.2.5 System Management

The *System Management* updates the system's state according to the user's condition. In this architecture, the component only performs data transmission control. However, it can be extended to include other system resource managements. The *System Management* receives the streaming data from the perception layer. It sends a complete set of the data to the *Plan* for decision-making at the edge and forwards a portion of the data to the *Analyze* for the re-training process at the cloud (see Figure 4.3d). The data transmission reduction is set via a management algorithm using a finite-state machine.

The algorithm includes  $n$  possible system's states and  $m$  patient's conditions. The current system's state is selected according to the user's condition and previous state. Figure 4.4 indicates an example of the management algorithm, where  $n$  and  $m$  are 4.  $S_1$  is the most cost-efficient state with most

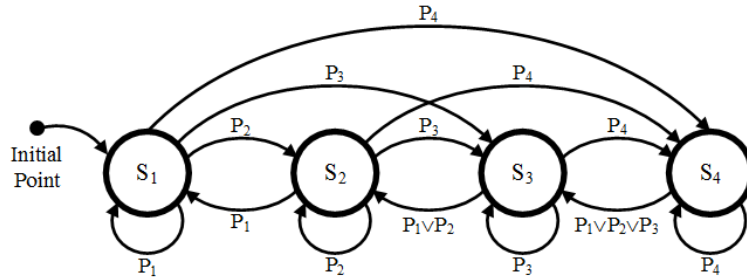


Figure 4.4: The state diagram of the management algorithm when there are four system's states ( $S_n$ ) and four user's conditions ( $P_n$ ).

data reduction, while  $S_4$  has no data reduction.  $P_1$  shows a normal health condition, whereas  $P_4$  is the worst condition. As indicated, the system state jumps to higher states in case of high-risk health condition detection. In contrast, the system state gradually decreases from a high state to lower states if health condition improves. For the sake of clarity, let us assume two examples.  $P_4$  is detected during the monitoring while the current state is  $S_1$  (i.e., most cost-efficient). Then, the state will be changed to  $S_4$  (no data reduction). In the second example, the current state is  $S_4$ , and the patient’s condition becomes normal ( $P_1$ ). Then, the state decreases, one step per iteration, to  $S_1$  ( $S_4$  to  $S_3$ ,  $S_3$  to  $S_2$ , and  $S_2$  to  $S_1$ ).

### 4.3 Case Study: Real-time Arrhythmia Detection

To evaluate the proposed architecture, a case study on real-time arrhythmia detection was utilized, focusing on continuous monitoring of patients suffering from cardiovascular diseases. The system was tested using existing datasets of ECG signals collected from Physiobank online databases [116, 161, 87]. The sensing part was emulated in this experiment by storing the data in a MicroSD card, reading the data by the ATmega328P microcontroller [18], and sending it to the gateway device via an RN-42 Bluetooth module [155]. The transmission was performed every 10 seconds, so a 10-second window of ECG signal was sent in each data transmission.

Two gateway devices with different specifications were selected to evaluate the architecture in different situations. The two devices were an NVIDIA Jetson-TK1 [170] as a single board computer and an HP Compaq 8200 Elite Linux machine, both of which run Apache web server, PHP, and Python interpreter services. The latter device provides better performance, relatively. The cloud server in this setup was a Linode virtual private server [141] enabled by two 2.50GHz Intel Xeon CPU, 4GB memory and SSD storage drive which runs an Apache web server on Ubuntu Linux.

The proposed system was compared with a baseline system enabled by a conventional Observe Decide Act (ODA) control strategy [106]. In this baseline system, the data was collected in the perception layer and was transferred to the cloud server for data analysis and decision-making. Then, the decision vector and notification were sent to the end-user (see Figure 4.5). The computing in the baseline architecture was limited to the cloud server, while the gateway device only acted as a communication bridge between the two other layers.

Two machine learning algorithms were selected in these experiments to investigate the efficiency of the architecture from different aspects. In the first setup, a linear Support Vector Machine (SVM) method [164] was leveraged to perform abnormality detection (simple binary classification) on the

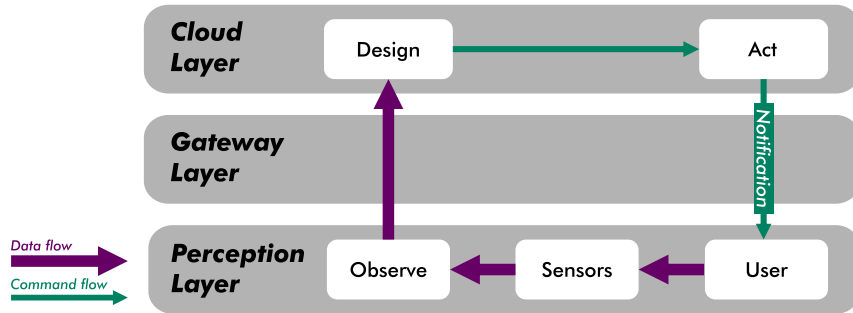


Figure 4.5: The baseline IoT system enabled by the ODA control strategy

signal. However, the second demonstration included a Convolutional Neural Network (CNN) [196] as a deep learning algorithm to detect different arrhythmias (multi-class classification).

### 4.3.1 Abnormality Detection

The linear SVM method enables real-time decision-making on the user’s health condition, classifying the incoming signals as *normal* or *abnormal* (i.e., signals with arrhythmia). In the design-time, the hypothesis function was trained at the cloud server (i.e., the *Analyze* component) using Scikit-learn [175] and Biosppy [38] libraries in Python. To this end, we used 10 hours of ECG signals collected from a healthy user and an individual suffering from cardiovascular diseases. For the training phase, 5 different features were extracted from each 10-second window of the signal and fed into the hypothesis function along with the signal’s labels (i.e., *normal* and *abnormal*). The extracted features were QRS complex duration, T wave duration, RR interval, PR interval, and ST segment (see Figure 4.6).

The hypothesis function was sent to the gateway device (i.e., *Plan* component). During the run-time, the incoming data (i.e., test data) were clas-

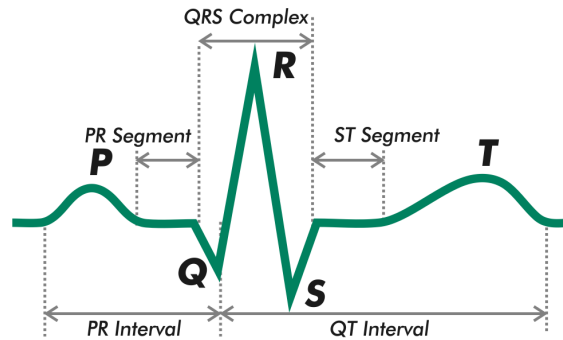


Figure 4.6: Temporal features of an ECG cycle



Table 4.1: Normalized confusion matrix

	Predicted value	
True value	TN = 0.97	FP = 0.03
	FN = 0.01	TP = 0.99

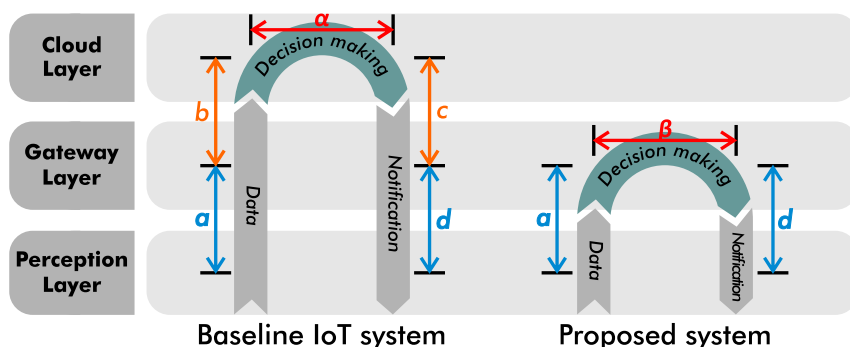


Figure 4.7: Notification flow in the baseline system and proposed system

sified locally and the decision vector was sent to the *Execute* component for the actuation. For the test dataset, emergency scenarios were simulated by adding ECG with arrhythmia at random points in the normal ECG. The data were chosen from 4 new users.

The classifier was validated by comparing the estimated labels with the true labels. The  $F_1$  score in the test data was 0.98. Table 4.1 indicates the obtained normalized confusion matrix. Consequently, the method was able to provide an acceptable performance differentiating normal and abnormal ECG signals.

The response time of the proposed system was evaluated in comparison to the baseline system. The response time is defined as the time interval between collecting the ECG signal and forwarding the notification to the user in the case of an emergency. Figure 4.7 shows the notification flows in the two systems. The baseline system includes transmission time between sensor and gateway device ( $a$  and  $d$ ), transmission time between the gateway device and cloud server ( $b$  and  $c$ ), and computation time at the cloud ( $\alpha$ ). However, the notification flow in the proposed method consists of transmission time between sensor and gateway device ( $a$  and  $d$ ) and the computation time in the gateway device ( $\beta$ ). The baseline system's response time was measured in different Internet networks, and the proposed system's response time was tested with the two gateway devices. As shown in Figure 4.8, the response time is considerably lower in the proposed system. In contrast, the response time of the baseline system is highly dependent on the available Internet network (i.e.,  $b$  and  $c$  values). The reduction of response time can improve

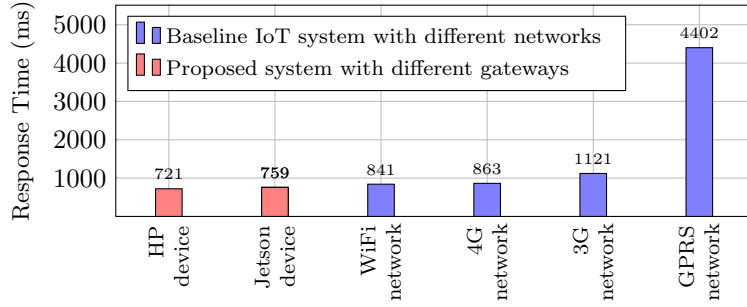


Figure 4.8: Response time in different approaches

the performance of the service and subsequently impact the user experience.

Moreover, the dynamic behavior of the system was evaluated in terms of bandwidth utilization and storage in the cloud. The data traffic rate is controlled by the *System Management* component as a function of  $\lambda$ , which is the portion of data that is sent to the cloud server when the user's condition is *normal*.  $\lambda$  varies from 1 to 6, where 1 indicates the lowest data transmission (i.e., sending one 10-second window of the ECG signal per minute) and 6 is the full data transmission (i.e., sending six 10-second windows per minute).

Table 4.2: Data traffic for one hour monitoring with different  $\lambda$  values

$\lambda$	Data to be transferred to the cloud (KB)	Data description (KB)	TCP overhead (KB)	Total traffic (KB)
1	439	29	13	481
2	879	29	25	933
3	1318	29	37	1384
4	1756	29	49	1836
5	2197	29	61	2287
6	2636	29	73	2738

Table 4.3: Data storage for one hour monitoring with different  $\lambda$  values

$\lambda$	Data in normal condition (KB)	Data in abnormal condition (KB)	Data stored in the cloud (KB)	Reduction in data size
1	406	355	761	71 %
2	787	355	1142	57 %
3	1167	355	1522	43 %
4	1549	355	1904	29 %
5	1929	355	2284	14 %
6	2310	355	2665	0 %

As represented in Table 4.2, the bandwidth utilization was significantly reduced (particularly if  $\lambda$  is 1) for 1-hour monitoring (with 8 minutes abnormality) in the proposed system. The total data traffic –including the data (i.e., ECG signals), Transmission Control Protocol (TCP) overhead, and data description– reduced to 19% if  $\lambda$  was 5 and to 82% if  $\lambda$  was 1. It should be noted that the data traffic rate was always at its maximum with different  $\lambda$  during abnormality detection, as the abnormal data was needed for further analysis in the cloud (e.g., re-training the classifier).

Similarly, Table 4.3 shows the reduction of the data stored in the cloud server during the 1-hour monitoring. The stored data reduced to 14% if  $\lambda$  was 5 and to 71% if  $\lambda$  was 1. As indicated, the data reduction was only performed when the user’s condition was *normal*. The proposed system could decrease unnecessary data storage in the monitoring. This data reduction is particularly important in long-term health monitoring, in which a large amount of data are collected throughout the monitoring period.

### 4.3.2 Arrhythmias Detection

In addition to a linear machine learning algorithm, the feasibility of deploying a non-linear algorithm in this architecture was assessed. The use of such algorithms enables multivariate and complex applications in the IoT-based health monitoring systems. The CNN, as a deep learning algorithm, was utilized to perform a real-time multi-class classification. In this regard, we implemented the algorithm proposed by Takalo-Mattila *et al.* [212] for the ECG signal classification. Using the TensorFlow library [1] in Python, the algorithm was trained in the *Analyze* component via a training dataset including 51020 ECG samples collected from different patients (design-time). The trained hypothesis function was sent to the gateway device to classify the incoming ECG signals into 5 classes as normal (N), supraventricular ectopic beat (SVEB), ventricular ectopic beat (VEB), fusion beat (F), and unknown beat (Q).

Table 4.4: Confusion matrix

		Estimated Decision				
		Normal	SVEB	VEB	F	Q
True Decision	Normal	<b>40671</b>	905	2615	68	0
	SVEB	642	<b>1148</b>	47	0	0
	VEB	339	2	<b>2874</b>	6	0
	F	275	0	111	<b>2</b>	0
	Q	2	0	5	0	<b>0</b>

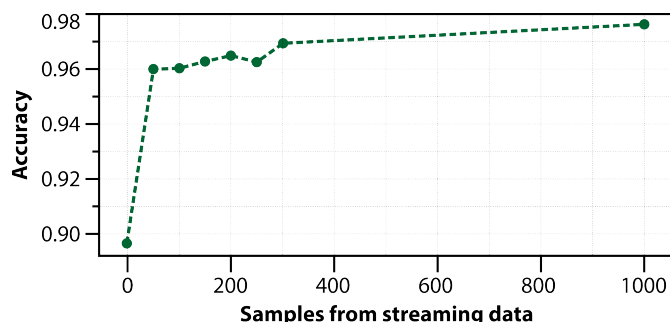


Figure 4.9: Accuracy improvement by re-training the model with new samples

The accuracy of the hypothesis function was evaluated at the beginning and during the monitoring. The monitoring was carried out utilizing ECG samples from new users whose data were not used in the training phase. In other words, the hypothesis function was generated from population data in the design-time. At the beginning of the monitoring, the accuracy was 0.89. The confusion matrix is indicated in Table 4.4. The correct classifications are relatively high although the accuracy might be inadequate for health decision-making. During the monitoring, the classifier was re-trained using the incoming signals. Therefore, the classifier was updated by seeing samples from the monitored person. As indicated in Figure 4.9, this process improves the accuracy of the classification, since the classifier becomes personalized to the monitored person during the monitoring.

Similar to the previous evaluation, the response time of the proposed system was also evaluated, compared with the baseline system. To validate the experiment, different setups were selected to measure the response time. In this regard, the response time of the baseline system was measured in different Internet networks ranging from the GPRS to the 4G network. Moreover, the response time of the proposed system was tested with different gateway devices. To this end, as the gateway, we used the Jetson-TK1 and HP Compaq 8200 Elite Linux machine. In addition, we also utilized an Oracle Virtual Machine (VM) with a single-core Intel Core i7 CPU at 3.4 GHz. The virtual machine (VM) was tested in the experiments by allocating 100%, 90%, 80%, 70%, 60%, and 50% of its execution capacity.

The response time of the two systems is illustrated in Figure 4.10. The baseline system had the shortest response time when the network was 4G; however, the response time increased by 3.2 times when the network was GPRS. In contrast, the shortest response time of the proposed system was for the VM with 100% core, and the longest response time was for the Jetson TK1. Consequently, the response time of the baseline system relies on the Internet connection which varies during the health monitoring. On

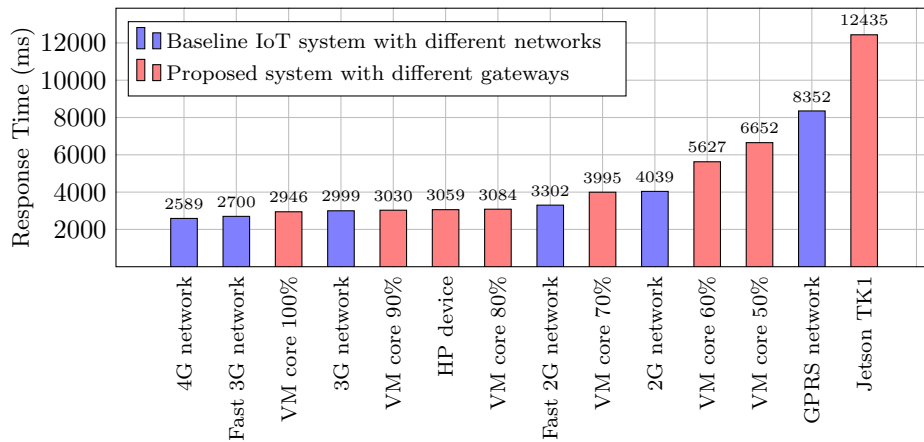


Figure 4.10: Response time for different approaches.

the other hand, the response time of the proposed system only depends on the processing power of the gateway device. Therefore, by choosing a suitable gateway device, the proposed system can guarantee an acceptable response time for the health application.

## 4.4 Summary

This chapter introduced a hierarchical computing architecture for IoT-based health monitoring. This architecture allowed the partitioning and executing of machine learning algorithms in IoT systems. Moreover, it included an autonomous closed-loop resource management technique to efficiently manage the flow of data in the system according to the user's condition. We utilized an enhanced version of the MAPE-K computing model as the backbone of this architecture to distribute various computing components in the 3-layer of IoT systems. A full system implementation was demonstrated for continuous monitoring of patients with cardiovascular diseases. The architecture was evaluated using two different setups enabled by linear and non-linear machine learning algorithms. The proposed architecture was compared with a baseline cloud-based architecture enabled by an ODA control strategy.

The results showed the feasibility of partitioning and executing of the linear and non-linear machine learning algorithms in this architecture, enabling local decision-making with acceptable response time. The proposed system improved the availability and latency of the health monitoring, compared with the baseline cloud-based system. The accuracy of the decision-making was also improved by personalization, where the classifier was periodically re-trained using the patient's data during the monitoring. Moreover, the dynamic behavior of the system reduced unnecessary data transmission to

the cloud, saving bandwidth utilization and cloud data storage, which are significant in the case of long-term health monitoring. Consequently, the improvements in the availability, response time, and bandwidth usage can have different positive impacts on the QoE of the IoT-based healthcare applications for both the patient and health provider.

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Figures 4.1–4.6, 4.8 and Tables 4.1–4.3 were taken from Paper III. Figures 4.7, 4.9, and 4.10 and Table 4.4 were taken from Paper IV.

## Chapter 5

# Data Fusion for IoT-based Health Monitoring

IoT-based systems necessitate a high-level of quality attributes to fulfill the requirements of ubiquitous health monitoring. Chapter 4 presented such attributes from a system-driven perspective, where a new computing architecture was proposed to provide acceptable attributes such as availability and adaptability. In other words, the contributions included the design of IoT-based systems for healthcare applications. In contrast, this chapter focuses on the system's attributes from a data-driven perspective, proposing a holistic complementary data fusion approach that can be deployed in IoT-based systems.

Missing data is one of the major problems in IoT-based health monitoring systems. It leads to an incomplete and inconsistent dataset and subsequently causes failure in the mission of health applications. Unfortunately, this problem is prevalent in IoT-based systems since data collection and data transmission are interrupted from time to time in these systems. One of the reasons for this can be that the users fail to wear the sensors, or the batteries of the devices (e.g., wearable sensors and mobile gateways) are exhausted during the monitoring period. In addition, the data might be corrupted due to artifacts generated by other surrounding resources. For example, hand movements might distort the PPG signals collected via wearable sensors [174, 167].

In this chapter, we address missing data in long-term health monitoring systems. We introduce a personalized missing data resilient approach which enables real-time health decision-making regardless of missing data. The proposed approach tailors multivariate data collection (i.e., heterogeneous data resources) in IoT systems and personalization to impute estimates with an acceptable bias for missing values. Subsequently, the estimates are utilized to complete the decision-making.

In the following, the missing data concept and the conventional methods of handling missingness in datasets are first outlined. Then, the missing data resilient approach for IoT-based systems is introduced. Finally, the proposed approach is evaluated using a case study on ubiquitous maternal health monitoring.

## 5.1 Missing Data

Missing data refer to data points in a given variable, whose values are absent. According to Little and Rubin [142], three missingness mechanisms produce missing values in a dataset. 1) Missing Completely At Random (MCAR): the missingness is independent of the missing value and available information; e.g., data is unrecorded due to a random system failure. 2) Missing At Random (MAR): the missingness is independent of the missing value although it is dependent on the available information; e.g., missing data is more probable when the sensor's battery level is low. 3) Not Missing At Random (NMAR): the missingness is dependent on the missing value; e.g., data with large values are missing as they are not in the sensor's range.

There is a broad range of studies on the analysis of missing data [25, 195, 203]. Various techniques have been proposed to handle missing data problems in databases, considering the types of missingness mechanism, the amount of missing data, and the application's requirements. However, many of these techniques are insufficient for health applications and cannot be applied in real-time settings.

Deletion techniques remove the samples in the data if there is a missing value. Listwise deletion and pairwise deletion are two straightforward deletion methods used in many studies [203, 150]. These techniques are easy to implement. However, they cannot be used in real-time applications, as no estimate is provided when there is a missing value. In addition to the deletion techniques, single imputation techniques are other conventional methods that impute the missing value according to the available data. Existing techniques in the literature include mean imputation, regression imputation, hot-deck imputation, Last Observation Carried Forward (LOCF), and K-Nearest-Neighbor (KNN) imputation [142, 13, 226]. These techniques are limited to the MCAR missingness mechanism, underestimating the variability of the missing values.

Moreover, modern techniques have been proposed to address missing data by considering uncertainty and variation in the data [25]. The multiple imputation method fills-in the missing value by generating different values with different uncertainties and integrating them into one estimate [142, 67]. Additionally, model-based techniques create models (i.e., hypothesis function) to estimate the missing values. In this regard, Maximum Likelihood



Estimation (MLE) was leveraged in different studies to estimate missing values via a likelihood function approximated according to the available data [165, 25]. MLE was used for the MCAR and MAR although other model-based methods such as pattern-mixture and shared-parameter models were proposed for the NMAR missingness mechanism [58, 113]. In addition, machine learning-based techniques train a hypothesis function to impute missing values. For example, SVM, neural networks, and genetic algorithms have been used in the literature to handle missing data [204, 21, 22].

Real-time health monitoring systems require a missing data analysis to handle the three missingness mechanisms, each of which could occur during the monitoring period. Therefore, the traditional algorithms cannot be deployed in these systems, as they are merely restricted to the MCAR mechanism. Existing modern algorithms use uncertainty in the analysis to include the MAR and NMAR. However, they are also insufficient for health monitoring since they cannot provide acceptable accuracy for health parameters such as heart rate, which changes dramatically and is highly dependent on other health and context parameters.

## 5.2 Personalized Missing Data Resilient Approach

This study proposes a personalized approach tackling missing data in real-time health monitoring systems. This approach performs data fusion in IoT systems to impute the missing value, leveraging heterogeneous data sources. The data sources include context information, historical data (i.e., past events), and meta-data (e.g., calendar events), each of which could correlate with the value of interest (i.e., missing value). These correlations are utilized in this approach to minimize the bias of estimates.

To show the function of the proposed approach, we consider an IoT-based system, in which the health parameters are remotely acquired from

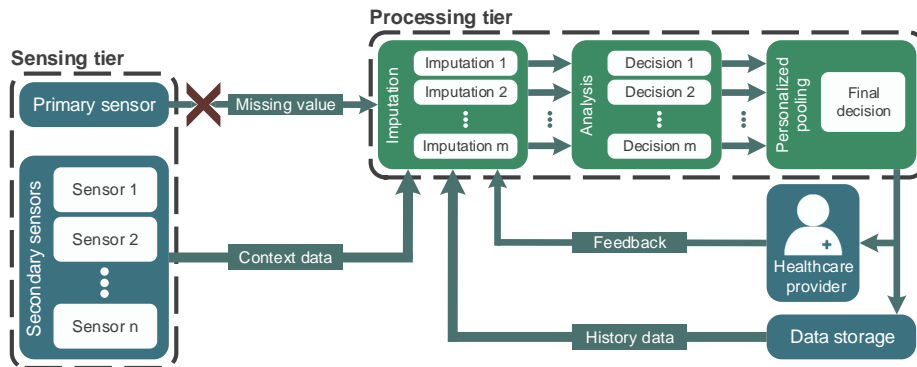


Figure 5.1: IoT-based missing data resilient approach

an individual. Figure 5.1 shows the integration of the proposed approach into the IoT-based monitoring system. The sensing tier includes a not-working sensor (i.e., primary sensor) which produces missing values and other sensors (i.e., secondary sensors) that collect context information. The system processes the available parameters and continuously provides the user’s health status (i.e., health decisions) for the healthcare provider.

In the processing tier, the multiple imputation as a modern method is employed to incorporate the data sources into the missing data analysis. In this regard, different values with uncertainties are generated. The estimates are utilized to produce different health decisions. Then, the decisions are pooled into one final decision. In the following, we will consider in detail the three main computing layers in this system, which are: *Imputation*, *Analysis*, and *Personalized Pooling*.

### 5.2.1 Imputation

Different estimates ( $m \geq 2$ ) are imputed for the missing value exploiting different imputation methods. The estimates are obtained from the available data sources which correlate with the primary data (i.e., missing value). The imputation methods are selected according to the nature of the missing data and the type of data sources. Three imputation methods are presented in the following, providing estimates for a health parameter.

#### Short-term Pattern

This estimate is generated by using patterns in the short-term historical data of the missing value. These patterns could significantly correlate with the missing value, particularly in health parameters such as heart rate. Autoregressive models can be leveraged in this regard, where the missing value is calculated from preceding neighbors [47]. Therefore, the missing value ( $x_t$ ) is defined as:

$$\begin{aligned} x_t &= f_s(t, \beta) \\ &= \beta_0 + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \cdots + \beta_n x_{t-n} \end{aligned} \quad (5.1)$$

where  $x_{t-1}, \dots, x_{t-n}$  are the  $n$  preceding neighbors, and  $\beta_0, \dots, \beta_n$  are the model’s parameters.

In the training process, the model’s parameters are determined using previous non-missing values of the primary data. The parameters desired are those that minimize the distance between the actual values and the estimates:

$$\sum_{i=1}^k [x_{t-i} - f_s(t-i, \beta)]^2 + \lambda \sum_{j=0}^n \beta_j^2 \quad (5.2)$$

where  $k$  is the number of training data,  $x_{t-i}$  is the actual data,  $f_s(\cdot)$  is the estimate from preceding data, and  $\lambda > 0$  is a regularization parameter [188, 173].

The estimated values are considered as the preceding neighbor in the next iterations. Therefore, the estimation errors are accumulated when one set of data points in a row is missing. Consequently, this imputation method is only appropriate when missing windows are small. Note that a missing window refers to the interval between the last available data point and the current data point.

### Context Information

The correlation between context information and the primary data is utilized. The context information indicates different states of the monitoring. The states can be defined with respect to the user's and system's conditions. Therefore, the missing value ( $x$ ) is estimated as:

$$x = f_c(t, \gamma) \quad (5.3)$$

where  $\gamma$  is the context data.

$f_c(\cdot)$  maps the context data (i.e., monitoring states) into the estimate. This function should be personalized, as the correlations are not similar in different people. Let us take an example where a heart rate value is missing, and the context is physical activity data. For one individual, her historical data shows a heart rate value of  $55 \pm 3$  during the sleep. In contrast, the heart rate value is  $65 \pm 5$  during the sleep of another person. Hence, the estimate is 55 for the first person and 65 for the second person if the heart rate value is missed during sleep. In consequence, the correlations ( $f_c(\cdot)$ ) between heart rate and different physical activity should be individually obtained in the monitoring according to her historical data.

### Lifestyle Pattern

Lifestyle patterns are other sources used to estimate the missing value. Similar windows of data are extracted from the available data and used for estimating missing data. These similarities can be obtained from manual and subjective measurements such as a user's calendar and medication information. For example, if the user's calendar shows this person attends a physical fitness course every day at 6 p.m., then, missing data in this time period can be estimated based on similar windows in the past.

Moreover, patterns can be obtained automatically, comparing the current window of data to previous data windows. In this regard, the missing value ( $x$ ) equals the corresponding value ( $x_k$ ) of the data window  $k$  that

has the minimum distance to the current window. The data window  $k$  is selected by the nearest neighbor rule:

$$\operatorname{argmin}_{k \in \phi} \operatorname{dist}(k)$$

where  $\operatorname{dist}(\cdot)$  is a distance function:

$$\operatorname{dist}(k) = \sum_{i=1}^n \|x_{i0} - x_{ik}\|^2$$

where  $n$  is the window length, and  $x_{i0}$  and  $x_{ik}$  are data points in the current window and window  $k$ , respectively.

### 5.2.2 Analysis

The decision-making approach is performed in this computing layer. This approach is repeated  $m$  times in each iteration because  $m$  estimates are generated for the missing value in the *Imputation* layer. In our case study,  $m = 3$  as three imputation methods (i.e., short-term pattern, context information, and lifestyle pattern) are considered. It should be noted that the estimates could be different due to the uncertainty and inaccuracy of imputation methods. Therefore, the decisions might be dissimilar.

### 5.2.3 Personalized Pooling

*Personalized pooling* is responsible for pooling the  $m$  decisions into one final decision. Conventionally, the pooling can be performed using an arithmetic mean. Therefore, the final decision is the average of decisions. This method leads to an inaccurate decision since the decisions with different errors are treated equally. To address this issue, a personalized pooling method is introduced to reduce the impact of decisions with a high error rate. The personalized pooling method leverages a weighted arithmetic mean. The weights are selected during the monitoring according to the decisions' uncertainties which rely on the conditions of both the user and system.

The weights are calculated when the primary data is available. In this regard, first, the imputation methods are utilized to estimate the primary data. Then, the actual value and estimates are compared, and imputation errors are calculated. The weights could be obtained by minimizing the sum of squared errors over all data points. However, this method is inappropriate for such dynamic systems, where both the user's conditions and system's states vary significantly during the monitoring. Therefore, in the proposed approach, the weights are determined based on these states in each imputation.

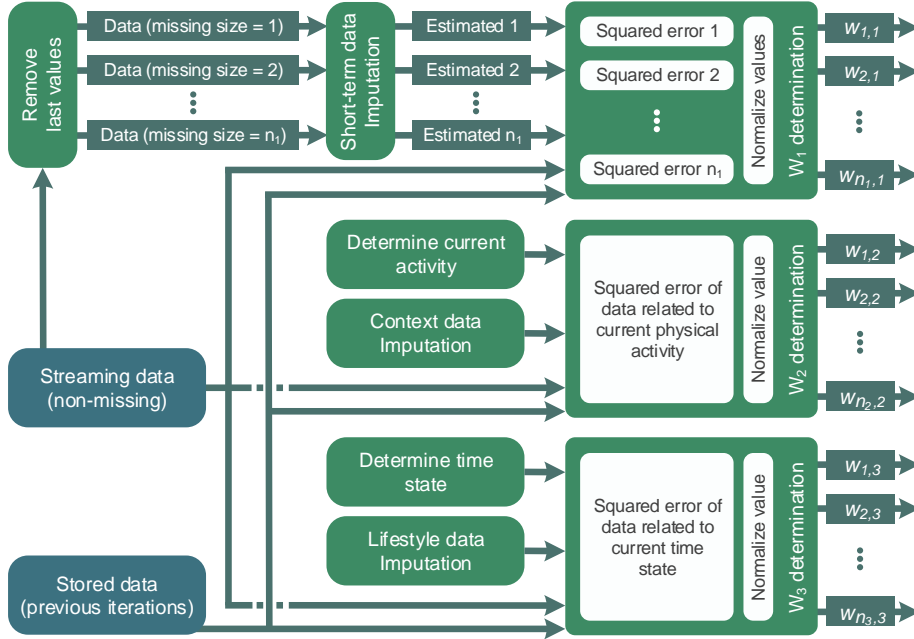


Figure 5.2: Weights determination in personalized pooling

For our case study, 3 different imputation methods are considered, so 3 weights vectors are specified when the primary data is available. The first imputation leverages short-term patterns and is highly dependent on the length of the missing window. Therefore, for each missing window size, an imputation error is obtained by calculating the distance between the actual value and estimated value. The corresponding weights are calculated for all the missing window sizes. Eventually, a vector of weights ( $W_1$ ) is specified for this imputation.

The second imputation utilizes the context information including different states. Therefore, a set of weights ( $W_2$ ) is defined for the context states. To determine the weights, it is possible to utilize the uncertainty (e.g., variance) of the estimates in different states. A smaller variance indicates the estimate is more likely to be close to the actual value. For example, the variance of heart rate during sleep (i.e., context information) is small during the monitoring. When the heart rate is missing during sleep, the estimate of this imputation is highly probable. Therefore, a large value is selected as the weight of this estimate.

The third imputation is associated with the lifestyle patterns. The current window is then compared with previous data (i.e., different time states) to determine the estimate. For each event (i.e., lifestyle pattern), the distance (i.e., squared error) between the actual values and the estimated values

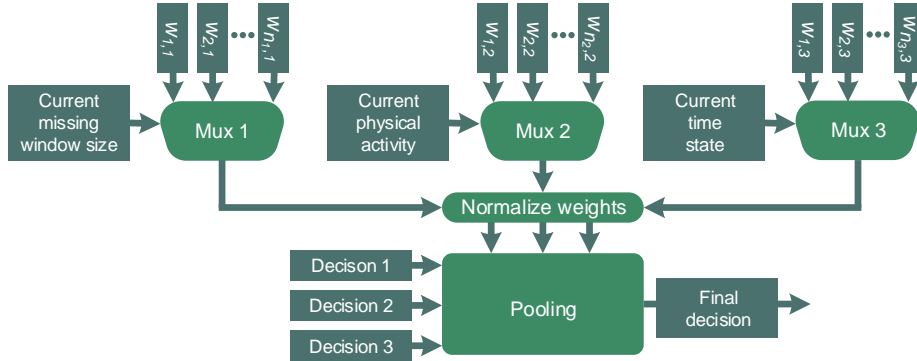


Figure 5.3: Weights selection in personalized pooling

is calculated. For instance, the distance is calculated for the working-days event, comparing missing data in this event with previous data in the same event. Eventually, the vector of weights ( $W_3$ ) is set for all the events. Figure 5.2 shows the weights determination in this computing layer.

When the primary data is missing, corresponding weights are selected from the weights vectors (i.e.,  $W_1$ ,  $W_2$ , and  $W_3$ ) according to the current missing window size, context state, and time state. Then, the final decision is determined using a dot product between the decisions and personalized weights. The weight selection and pooling process are indicated in Figure 5.3.

It should be noted that a late fusion is selected over an early fusion in this method, as the objective is to minimize the error (biased) of the final decision and not the missing values. Therefore, the pooling weights are updated throughout the monitoring according to the distance between the estimated and actual decisions.

## 5.3 Case Study: Maternal Health Monitoring

The proposed missing data resilient approach was evaluated by implementing a case study on maternal health. The case study includes a real human subject trial, in which 20 primiparous pregnant women were remotely monitored for 7 months.

### 5.3.1 Recruitment and Setup

The women were selected in one of two maternity outpatient clinics in Southern Finland between May and September 2016. The inclusion criteria were:

- The participant is at least 18 years old.

- She expects her first child.
- The pregnancy is singleton.
- The gestational age should be less than 15 weeks.
- She owns a smartphone, tablet, or personal computer.
- She understands Finnish or English.

Twenty-two pregnant women met the criteria although twenty women agreed to participate in this maternal monitoring. In face-to-face meetings, the purpose of the study and the procedure were provided for the pregnant women. Moreover, background information –including age at the pregnancy, body mass index, and marital status– was collected. Then, the instructions were given to the women.

An IoT-based system was utilized in this study to continuously collect and analyze the health conditions of the pregnant women. The data collection was performed via Garmin Vivosmart® HR [83]: a small lightweight energy-efficient wristband. The device consists of a built-in PPG sensor to acquire heart rate, and an Inertial Measurement Unit (IMU) to track steps and physical activity. The data collection rate was set to one sample of data per 15 minutes. In addition, subjective data collection was obtained via semi-structured phone interviews once or twice in a month. The interviews were implemented to improve the analysis. The data transmission was carried out through gateway devices which were either smartphones or personal computers in our setup. The data analysis was performed by a Python service in the cloud server that is a Linode virtual private server [141] enabled by two 2.50GHz Intel Xeon CPU and 4GB memory.

The monitoring period was around seven months for each participant. The participants utilized the wearables for an average of 182 days, and the daily use was on average 17.9 hours during the second trimester, 16.7 hours during the third trimester, and 14.4 hours during the postpartum. The monitoring was ended in June 2017. More details about this monitoring can be found in [94].

## **Ethics**

The study was conducted in accordance with the code of ethics of the World Medical Association (Declaration of Helsinki) for involving human subjects in the experiments. It was also approved by the joint ethics committee of the hospital district of Southwest Finland (35/1801/2016) and Turku University Hospital (TYKS). Moreover, the written informed consent was obtained from all participants enrolled. In addition, the permission to use Garmin Vivosmart® HR (Garmin Ltd, Schaffhausen, Switzerland) in this study was acquired from the manufacturer Garmin Ltd.

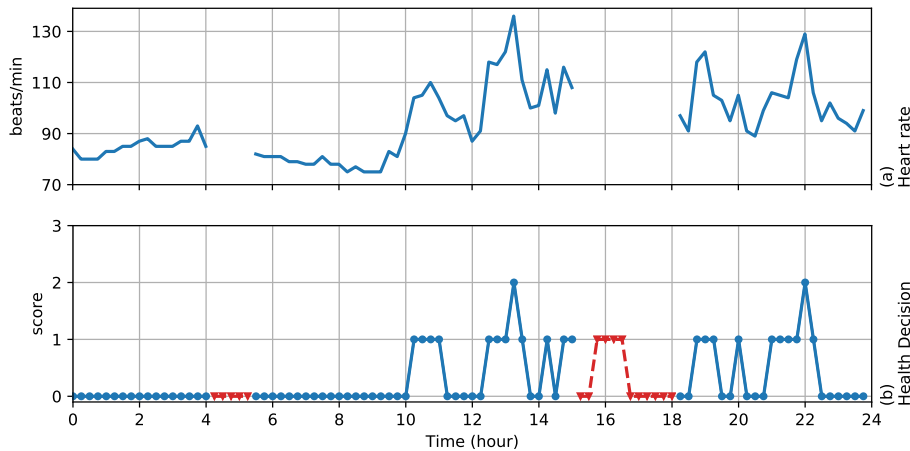


Figure 5.4: A 24-hour sample of monitoring with missing heart rate values and estimated health scores. The blue circles are the scores when heart rate is available, and the red triangles represent estimated scores when the heart rate values are missing

### 5.3.2 Missing Data Resilient Approach

The proposed approach was implemented using a rule-based indicator, mapping the sensor data into a health decision. In our setup, the indicator generated a warning score between 0 and 3, where 0 referred to a normal health condition, and 3 indicated the highest health risk. For each woman, the rule-based indicator was defined utilizing her individual data (e.g., baseline heart rate at the beginning of the monitoring) and a set of guidelines and rules in maternal health and obstetric EWS [111, 152, 68, 53, 159].

The primary data was the heart rate in this setup, and the output was the warning score (see Figure 5.1). The approach continuously delivered the scores despite missing heart rate values in the monitoring. A 24-hour sample of the monitoring is shown in Figure 5.4, where heart rate values are missing in a 75-minute and a 180-minute time-windows. The blue circles (solid line) represent the scores when the heart rate values are available, and the red triangles (dashed line) are estimated health scores while the heart rate values are missing.

### 5.3.3 Accuracy Assessment

In this section, the performance of the proposed approach is investigated in comparison with existing approaches. Using the SciPy [120] and Scikit-learn [175] libraries in Python, four different missing data analysis techniques were implemented to estimate missing heart rate values and obtain



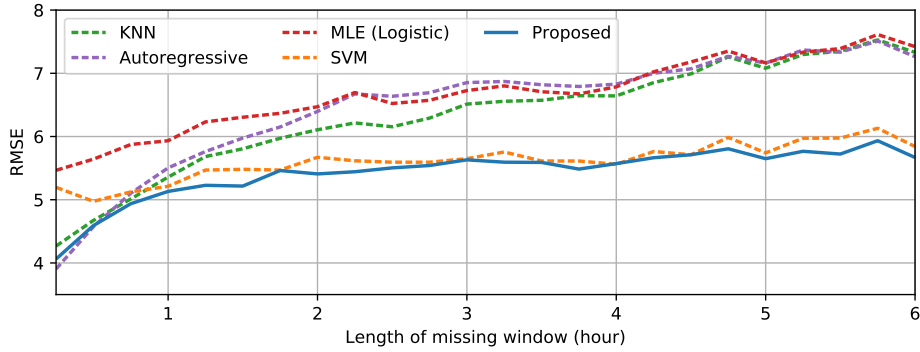


Figure 5.5: RMSE values of the proposed and existing approaches while the missing window varies from 15 minute to 6 hours

health scores. The techniques used were 1) the KNN (a single imputation technique) to impute missing heart rate using  $k$  preceding non-missing neighbors weighted by the inverse of distance to the missing value; 2) the autoregressive model (a single imputation technique) to impute the data using preceding values; 3) the MLE (a model-based method) to estimate the missing value using a Sigmoid function; and 4) the SVM (a machine learning algorithm) to fill in the missing value utilizing a radial basis function (RBF) kernel and the user’s historical data (i.e., last two-week data).

We evaluated the accuracy of the decision-making (i.e., warning score) when the heart rate was missing. To this end, a cross-validation technique was utilized to remove windows with heart rate values of different sizes. The window sizes varied from 15 minutes to 6 hours. Then, the actual scores and estimated scores were compared. This process was repeated for the proposed approach and other techniques in 2040 iterations for the data of 15 (out of 20) pregnant women. The data of 5 women were excluded from the evaluation, as the missing data was too large (i.e., more than half of the monitoring). For comparison, two metrics were utilized.

First, the Root Mean Square Error (RMSE) of the estimates was calculated, representing the distance between estimated scores and actual scores. Figure 5.5 shows the RMSE values of the proposed approach and state-of-the-art techniques for different missing windows. When the missing window is small, the proposed approach, KNN, and autoregressive methods obtain the lowest error although the errors of the SVM and MLE are relatively higher. When the missing window is increased, the RMSE values of all the methods become larger. As indicated, the KNN, autoregressive, and the MLE methods have high error rates in case of large missing windows. In contrast, the RMSE of the proposed method is the lowest.

Second, the Concordance index (C-index) [90] of estimates were com-

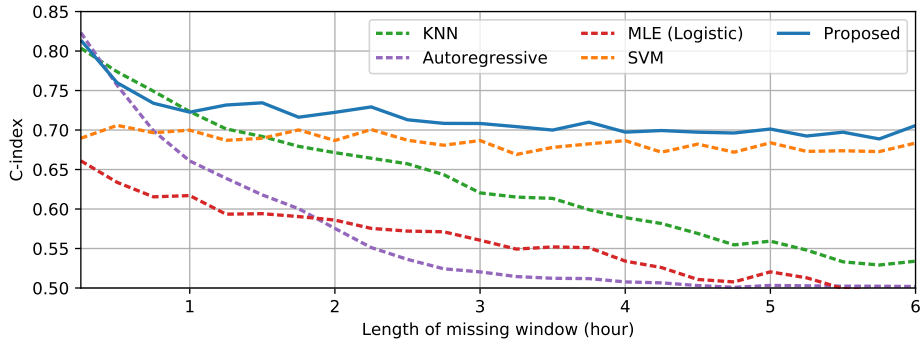


Figure 5.6: C-index values of the proposed and existing approaches while the missing window varies from 15 minute to 6 hours

puted, indicating how well the estimates (i.e., health scores) were produced considering the order of the scores. It is important to keep in mind that in this decision-making, health scores are in an ascending order, where 0 is the normal condition, and 3 is the highest health deterioration. The C-index values for the methods are illustrated in Figure 5.6. The MLE has the lowest C-index, and the best C-index values of the SVM method is 0.71. When the missing window is small, the C-index of the KNN and autoregressive are relatively high although the values drop to less than 0.55 in case of large missing windows. In contrast, the proposed approach has the highest C-index. As indicated, the C-index is 0.82 when the missing window is small, and the value reduces to 0.7 when the missing window size increases to 6 hours.

As indicated, the proposed approach obtains more accurate estimates in comparison to the existing methods. The approach benefits from using different resources to estimate the final decision. The main concern of using such resources (particularly context information) in the computation is that possible low correlation between the missing value and the external source might affect the final decision. The proposed approach tackles this problem using the personalized pooling technique, where a small weight is selected if the correlation is insignificant. For example, a low value is selected (as the weight of context information) when the user is in vigorous or moderate activities, since the variation of the heart rate values are high (high variance).

The rule-based indicator proposed was a proof of concept for the missing data resilient approach. Inclusion of more context information (e.g., different vital signs) can reduce the bias of estimates. The proposed approach can also be adapted to other domains, where multivariate data with correlations are collected. Examples are smart public transport applications, in which multi-sensor IoT systems are utilized, and one sensor might fail throughout

the monitoring. Hence, the decision-making can be enabled despite the occurrence of missing data.

## 5.4 Summary

This chapter proposed a complementary data fusion approach to tackle the missing data problem in long-term health monitoring systems. The proposed approach leveraged various data resources in IoT-based healthcare systems to estimate missing values, providing real-time decision-making despite the occurrence of missing data. The approach utilized the multiple imputation method 1) to impute the missing value via different methods, 2) to generate different decisions using the estimated values, and 3) to pool the decisions exploiting a personalized pooling method. The approach was designed and developed for a real human subject trial on maternity health, where decisions regarding the mothers' health status were delivered continuously despite missing heart rate values in the monitoring.

The proposed approach was compared with conventional missing data analysis techniques to investigate the accuracy of the decisions. The obtained results showed that the proposed approach had the best performance in different missing window sizes. The approach could tailor different data sources in IoT-based systems to consider the variability of missing values in the estimates. The improvement was highly significant when the imputations and pooling processes became personalized through the monitoring. In consequence, the proposed approach enabled real-time missing data imputation with an acceptable bias, leading to improvement in the resilience and accuracy of the IoT-based healthcare systems.

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Figures 5.1–5.6 were taken from Paper V.



## Chapter 6

# Patient Modeling in IoT-based Health Monitoring

Chapter 5 presented how data analytic approaches tailor the IoT system's benefits (e.g., heterogeneous data collection) to satisfy various quality attributes in health monitoring systems. In this chapter, the developments are considered from another perspective, a proposal to use individualized decision-making and effective care in long-term monitoring.

Conventionally, decision-making methods including guidelines, rules, and models are determined according to population data. This general decision-making could lead to inaccurate results, as health conditions might be specific to one person. For example, a resting heart rate equal to 80 beats per minute could be abnormal in general although it could be normal for a person with a specific condition. Ubiquitous health monitoring can provide data collection from the user in everyday settings for a long period of time. Such data can be leveraged to carry out personalized decision-making, where the user's historical data are included in the analysis. Therefore, the system can perform specifically for every user addressing their needs.

This chapter proposes a personalized model for sleep quality assessment throughout the pregnancy and postpartum. The model provides an explicit representation of sleep quality, by which trends and abnormal events of sleep data can be extracted by considering the user's historical data. To demonstrate the function of the personalized model, we conducted a case study on remote maternal sleep monitoring, where the sleep data of 13 pregnant women were collected and analyzed for six months of pregnancy and one month postpartum. In this monitoring, we first exploited a semi-supervised learning algorithm to train a model for each individual using her own data at the beginning of the monitoring (i.e., eight weeks of data from the pregnancy). Then, the trained models were employed to evaluate sleep adaptations in the rest of the pregnancy and postpartum.

In the following, the state-of-the-art sleep monitoring methods in the literature are first discussed. Then, the personalized sleep model is introduced. Finally, the implementation on the collected sleep data of the case study is presented. The personalized model is also evaluated and compared with a baseline method.

## 6.1 Maternal Sleep Monitoring

Sleep is a complex and vital process, which significantly impacts bodily function and quality of life [221, 39, 172]. Sleep indicates the overall health and well-being of a person. Monitoring of sleep has an important role in home- and hospital-based health applications. In this regard, various qualitative and quantitative sleep monitoring techniques have thus far been proposed in both clinical and commercial medical applications [200, 126, 139].

For pregnant women, the importance of sleep monitoring is even more significant, as their bodies and sleep cycles are highly affected by substantial physiological and hormonal changes during and after the pregnancy period. For instance, disorders of maintaining sleep and restless legs syndrome are particularly prevalent during pregnancy [177, 148, 104]. These changes might lead to sleep disturbances and subsequently to health problems and adverse pregnancy outcomes. Maternal sleep quality assessment could be the first step to address and mitigate such disturbances and potential complications [206, 157].

Several studies have investigated maternal sleep in pregnancy and postpartum. Traditionally, sleep has been monitored via subjective measurements, in which the users were asked to answer different questions, describing their sleep experiences. For example, the Pittsburgh Sleep Quality Index (PSQI) (the gold standard) [36] and the Berlin Questionnaire [214] are self-report screening questionnaire used to differentiate “good” and “bad” sleep quality. These measurements are broadly used in the literature as they are simple and easy to implement [104, 70, 206, 157, 84, 235]. However, they might result in poor performance or biased outcomes because the methods are merely restricted to subjective and qualitative data [132, 101, 100, 24].

On the other hand, objective measurements have been introduced for sleep quality assessment of pregnant women. These methods tailor the user’s body movements and health parameters to extract sleep attributes such as sleep duration and sleep stages. PSG is the gold standard of the objective methods, in which multi bio-signals such as ECG, EEG, and EOG are acquired in the study of sleep. Unfortunately, the PSG is impractical for in-home applications and longitudinal studies due to its complex and burdensome data collection setup. For maternal sleep, the method has been limited to one- or two-day monitoring studies [137, 214]. Alternatively,

actigraphy is another method for sleep quality assessment. This method employs small wearable devices enabled by an IMU to track body movements and physical activities. The devices can be placed on the user's thigh, ankle, or wrist. The actigraphy is straightforward and more convenient than the PSG. Standalone actigraph devices with no network connectivity have been used in different studies to monitor maternal sleep for up to two weeks [136, 54, 216, 98].

Longitudinal sleep monitoring requires a long-term data collection of individuals in everyday settings. As discussed in previous chapters, IoT-based systems can perform such data collection. These systems can employ both the subjective and objective measurements into the sleep quality evaluation. Thanks to the advancements in embedded systems and wearable electronics, several devices (e.g., smartwatches and smart wristbands) can be exploited in this regard, through which body movements and health parameters can be recorded.

The IoT-based system can provide multi-parametric monitoring of daily sleep, including several sleep attributes whose volumes dramatically increase over time. Such data, as rich sources of sleep assessment, can be traditionally analyzed, where sleep attributes are investigated separately. For example, the relationship between short/long sleep duration (as a sleep attribute) and high-risk diseases has been investigated in different studies [119, 219]. These conventional methods examine the sleep quality from a single perspective. However, such multivariate data necessitate an intelligent approach to analyze sleep quality holistically. This approach should integrate multi sleep attributes into an overall sleep score. This score would then allow a better understanding of the sleep quality in a care routine, from which the trends, variations, and special events in the sleep periods are determined. In the following, we address this need by proposing a personalized sleep model.

## 6.2 Personalized Sleep Model

This section proposes a personalized sleep model to investigate sleep trends and abnormalities during and after pregnancy. In this regard, the model is created exploiting an anomaly detection method. Anomaly detection methods could be appropriate for such purposes, where a model is trained to discriminate abnormal data samples from normal ones. There is a wide range of anomaly detection methods in the literature, utilized in different fields such as fraud detection, cybersecurity, and healthcare [2]. However, many of them are inapplicable to this study. In the following, first, existing anomaly detection methods are briefly discussed. Then, an appropriate method is selected to develop the sleep model. The method selection depends on different factors including the type of anomalies, type of training

samples, and the method’s output.

According to the type of anomalies, the existing methods are partitioned into 3 classes [45]. 1) Point anomalies: a data sample is abnormal if its attributes are too far from other data samples. 2) Contextual anomalies: a data sample is only abnormal in a certain context. Therefore, the abnormality is specified based on the context information. 3) Collective anomalies: a group of related data samples is anomalous with respect to other data samples. In our study, we investigate abnormalities in daily sleep, where a data sample includes sleep attributes from a single night. Therefore, point anomalies methods are applicable.

The anomaly detection methods are also categorized based on the data involved. Supervised methods use labeled data (i.e., “normal” and “abnormal”) to generate a model for abnormality detection. In this regard, neural networks, SVM, and rule-based techniques have been introduced in the literature [97, 49, 72]. In contrast, unsupervised methods are utilized for unlabeled data [28, 140]. These methods consider that “normal” data occur more often than “abnormal” data. Therefore, they differentiate the abnormality if a sample is very different to the entire dataset. On the other hand, semi-supervised methods employ one-class machine learning methods to construct the model [149, 44, 103]. The data are also unlabeled in these methods. However, the training data samples are considered as “normal”, and the test data samples are categorized as “abnormal” if they are very divergent to the trained model. In our study, the data is unlabeled; the goal being to create personalized models to compare the sleep data of individuals with their own data. Therefore, our selection is reduced to semi-supervised methods.

In addition, anomaly detection methods determine the abnormality, by producing binary (i.e., “normal” and “abnormal”) or continuous outputs. In our study, the model is required to estimate the degree of abnormality throughout the pregnancy period, and therefore, techniques with continuous output are only applicable.

Considering the inclusion criteria of our study, Replicator Neural Networks (RNN) as a semi-supervised method is an appropriate option. The method considers the training data as “normal” data points. Then, the abnormality levels of the test data samples are obtained using the trained model. To this end, the model provides scores whose values are proportional to the abnormality level of test data samples. The RNN method was first introduced by Hawkins *et al.* [103] and was later developed by Dau *et al.* [57]. The RNN works well with high dimensional data although a small number of training samples might affect its performance negatively.

To address this issue, Bayesian methods can be integrated into the RNN method. Using Bayesian methods in neural networks was first proposed by MacKay [146] and Neal [169]. Bayesian methods consider probability



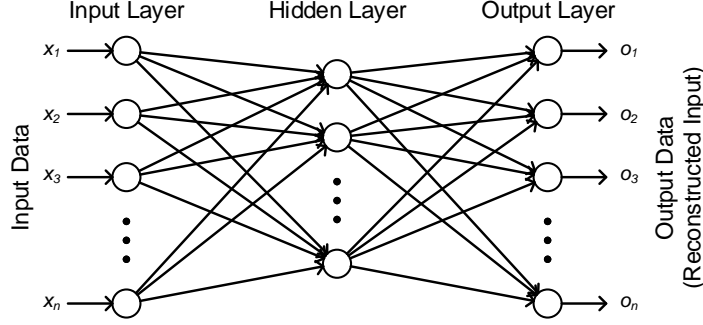


Figure 6.1: RNN with one hidden layer

distributions in the computation, providing an uncertainty along with the estimate. Therefore, the method is robust to over-fitting, and its performance can be improved when there are fewer training data samples [80].

In the following, we first observe how the personalized sleep model is constructed using the Bayesian RNN method. Then, the abnormality score calculation is outlined.

### 6.2.1 Model Construction

The RNN method is an auto-associative neural networks, representing how data features are related. It extracts a non-linear representation of the data and then reconstructs the input data at the output. During the training phase, the weights in this neural networks method are optimized to minimize reconstruction errors of the training data. The error for a single data sample is specified as:

$$\delta_i = \frac{1}{n} \sum_{j=1}^n (x_{ij} - o_{ij})^2 \quad (6.1)$$

where  $n$  is the number of features,  $x_{ij}$  is the input data sample, and  $o_{ij}$  is the method's output which is the reconstructed input data. In an ideal situation, the reconstruction errors are zero, so the trained model can perfectly reproduce the training data at the output.

The Bayesian RNN method in this study is designed with one hidden layer, as shown in Figure 6.1. Given the input data points as  $X = \{x_1, \dots, x_m\}$ , the output of the units of the hidden layer are calculated by:

$$h(X) = g(W_1 X) \quad (6.2)$$

where  $W_1$  is the first weights vector, and  $g(\cdot)$  is the rectified linear unit (ReLU); i.e.,  $g(z) = \max(0, z)$ . Moreover, the output of the units of the output layer are:

$$f(X) = g(W_2 h(X)) \quad (6.3)$$

where  $W_2$  is the second weights' vector. The weight vectors are defined over probability distributions.

We need to determine the posterior distribution of the weights, therefore,  $p(w|X, Y)$  can be defined as:

$$p(w|X, Y) = \frac{p(Y|X, w)p(w)}{p(Y|X)} \quad (6.4)$$

where  $p(w)$  is a prior probability distribution of the weights (i.e., a Gaussian probability distribution in our setup),  $p(Y|X, w)$  is the likelihood obtained by updating our beliefs about the prior after seeing the data, and  $p(Y|X)$  is the model evidence.

However, as the model evidence is intractable for most real-life problems [80, 32], Equation 6.4 cannot be used. In this regard, an approximating distribution (i.e.,  $q(w)$ ) is computed utilizing an approximation method such as Variational Inference [121].  $q(w)$  is defined as:

$$q(w) = p(Y|X, w)p(w) \quad (6.5)$$

$q(w)$  should be close to  $p(Y|X, w)$ , so the Kullback–Leibler divergence (KL divergence) [128] of the two distributions should be minimized:

$$KL(q(w)||p(w|X, Y)) = \int q(w) \log \left( \frac{q(w)}{p(w|X, Y)} \right) dw \quad (6.6)$$

Unfortunately, the KL divergence is also intractable, because it still includes the model evidence. Therefore, Evidence Lower Bound (ELBO) as an alternative to the KL divergence is utilized.

$$ELBO = \int q(w) \log p(Y|X, w) dw - KL(q(w)||p(w)) \leq \log p(Y|X) \quad (6.7)$$

The ELBO is the negative of the KL divergence up to a logarithm constant, thus maximizing the ELBO is equivalent to minimizing the KL divergence. For more details, see [80, 32, 127].

### 6.2.2 Score Calculation

During the testing phase, the test data are reconstructed using the trained model. As the model is a compressed representation of the training data samples, the reconstruction errors show the abnormality levels of the test data. For the sake of clarity, let us assume two examples. In the first example, the reconstruction error is small for a test data sample, and this small error shows that the sample is close to the model (i.e., training data). Hence, the abnormality level is low. In the second example, the reconstruction error is large for a test data sample. This error indicates that the sample is new

to the model. In other words, the model did not see similar data samples in the training phase. Therefore, the abnormality level is high.

Consequently, we calculate the abnormality score (i.e., abnormality level) for each test data sample according to the reconstruction errors as follows:

$$s = \frac{1}{n} \sum_{j=1}^n (x_j - o_j)^2 \quad (6.8)$$

where  $n$  is the number of data features,  $x_j$  is the original data sample and  $o_j$  is the reconstructed data sample.

### 6.3 Case Study: Maternal Sleep Quality Assessment

The proposed method is tested using a case study on maternal health. The case study was also utilized in Chapter 5, to evaluate the proposed missing data resilient approach. In contrast, this chapter focuses on the sleep quality of mothers during the monitoring. As presented in Section 5.3.1, we exploited an IoT-based system that employed the Garmin Vivosmart® HR [83] as a feasible device for long-term health data collection. The sleep data analysis was performed by a Python service in the cloud server (i.e., a Linode virtual private server [141]). The Python service, enabled by the Lasagne [134] and PyMC3 [181] libraries, was responsible for both the model construction and score calculation.

As mentioned in the previous chapter, the monitoring was performed on 20 primiparous pregnant women for 7 months. It started from week 13 in the pregnancy until week 4 postpartum. Unfortunately, the sleep data of 7 participants were insufficient because they refused or forgot to wear the device during the nights. Therefore, we only included the sleep data of 13 women in this sleep analysis.

The sleep event in each day was obtained from the sleep information provided by the Garmin device. To validate the sleep information, it was manually cross-checked and compared with other data resources such as body movements and heart rate values. Then, if no match was found, the sleep information was updated or removed. Moreover, for simplicity, the sleep events with missing values were omitted using a Listwise deletion method. For the 13 women, valid sleep events from  $172.15 \pm 33.29$  days per person were derived out of the total  $216.61 \pm 14.34$  days of the monitoring (79.5%).

For each sleep event, eight sleep attributes were extracted leveraging the sleep information, body movement data, and heart rate values. Moreover, step counts data were also used to determine the amount of time that the user spent in bed. Table 6.1 lists the eight attributes derived from each

Table 6.1: Eight attributes derived from each sleep event in this study

Sleep attributes	Definitions
Sleep Duration	The total time of the sleep event in a day
Sleep Onset Latency (SOL)	The amount of time in bed before the sleep event starts
Wake After Sleep Onset (WASO)	The amount of time that the user is awake after the sleep event starts and before the event ends
Sleep Fragmentation	The number of awakenings after the sleep event starts and before the event ends
Sleep Efficiency	The ratio of the total time of the sleep event (i.e., Sleep Duration) to the total bedtime
Sleep Depth	The ratio of the deep sleep duration to the total time of the sleep event (i.e., Sleep Duration)
Resting Heart Rate	The number of heart beats per minute in the sleep event while the user is at complete rest
Heart Rate Recovery	The amount of time between the start of sleep event and the resting heart rate is reached

sleep event and indicates how they are defined in this monitoring. The sleep attributes allow representations of the quality of sleep events from different perspectives. These attributes were then fed into the proposed method.

For the training process, the personalized sleep model was trained for each individual, using the person’s sleep data at the beginning of the monitoring. As we were using a semi-supervised algorithm, the training data were considered as “normal” data. In this monitoring, the training data were the sleep events from week 13 to 21 in the pregnancy, since they were the closest to the user’s normal condition. However, in ideal situations, the sleep data of pre-pregnancy should be considered as the training data.

For the testing process, the trained model was applied to the data collected during the rest of the monitoring, which was the data from week 22 of the pregnancy to week 4 postpartum. Then, the sleep scores were calculated, showing the degree of sleep abnormality. Figure 6.2 illustrates the sleep abnormality scores of the 13 pregnant women. The median values, indicated by the solid red line, increased during pregnancy. It shows sleep abnormalities –sleep changes in comparison to the beginning of the monitoring– are more frequent as pregnancy progresses. The score indicates the highest sleep degradation at week 1 postpartum. The maternal sleep quality moderately enhanced after week 1 postpartum, even though it was notably worse than the sleep quality during the pregnancy. In comparison to the existing longitudinal (subjective) sleep quality assessment studies [157, 104, 197, 70], these results show the variations of maternal sleep during pregnancy and

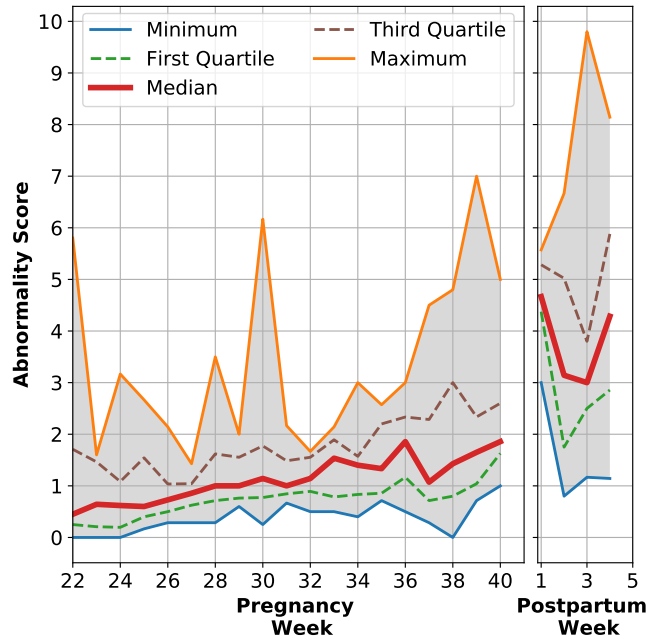


Figure 6.2: The abnormality score of mothers of week 22-40 in the pregnancy and week 1-4 postpartum

the postpartum with a *higher confidence level*, obtained from *long-term* and *fine-grained* quantitative measurements and analysis.

### 6.3.1 Model Evaluation

The evaluation is specified according to the general hypothesis behind the model. As mentioned previously, the proposed method leverages a semi-supervised technique, where the training data are labeled as “normal,” and the test data are unlabeled. The model produces scores as outputs for the test data, showing their abnormality levels. The scores should be proportional to the users’ sleep changes, compared with their own data.

The proposed method was evaluated in comparison with a baseline method which was a simple aggregate method. The baseline method determined the abnormality score, using overall population attributes in normal conditions. These population attributes were the average sleep attributes of all the participants at the beginning of the pregnancy (i.e., the training data in the proposed method). In this regard, the abnormality score for a sleep event was calculated as the sum of the normalized distance between its attributes and the overall population attributes.

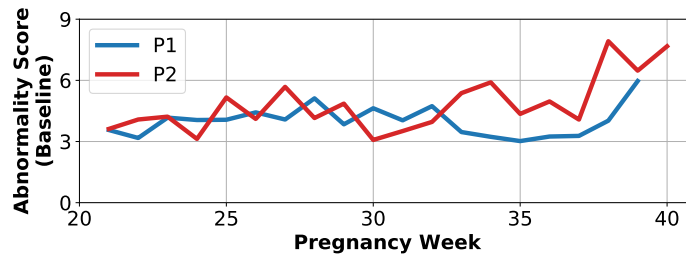
The performance of both methods was evaluated using the sleep data of two pregnant women (i.e., P1 and P2) who had different conditions during

Table 6.2: Attributes of P1 and P2 along with the ratio of the attributes at the end of pregnancy to her own data and to the population data.

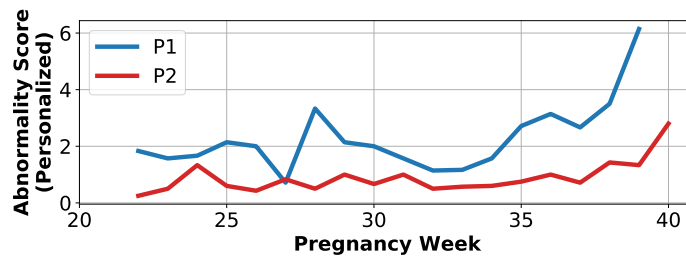
Attributes	#	Mid of second trimester	End of third trimester	Ratio to population data	Ratio to her own data
Sleep fragmentation (times)	P1	0.5	1.53	1.62	3.06
	P2	1.39	2.29	2.43	1.64
WASO (minutes)	P1	15.3	37.32	1.48	2.43
	P2	34.39	75.83	3.02	2.2
Sleep duration (minutes)	P1	389.34	341.25	0.71	0.87
	P2	480.04	456.33	0.95	0.95
Resting heart rate (beats/min)	P1	53.38	59.23	0.96	1.2
	P2	65.61	71.17	1.16	1.08

the monitoring. P1 had notable sleep changes, but P2 experienced fewer changes in her sleep attributes. The variations in the sleep attributes of P1 and P2 are indicated in Table 6.2. As shown, the ratios of P1 attributes at the end of pregnancy to her own attributes in the mid of the second trimester are considerably higher than the ratio of P2.

The abnormality scores calculated by the methods during the pregnancy



(a) The baseline method



(b) The proposed method

Figure 6.3: The abnormality scores of two participants, obtained from the baseline and proposed methods

are illustrated in Figure 6.3. The baseline score shows that P1 and P2 have similar sleep changes during pregnancy, which is wrong according to their sleep attributes. Therefore, the baseline score cannot indicate the sleep changes of P1. The reason is that the baseline score was obtained using the population data, and P1's sleep changes were relatively less when compared to the overall population attributes (see the ratio to population data of P1 in Table 6.2).

On the other hand, the proposed method was able to discriminate between the sleep data of P1 and P2 correctly. As indicated in Figure 6.3b, the abnormality scores of the personalized method show that sleep changes of P1 are considerably more significant than the sleep changes of P2. Moreover, the sleep changes of both participants also increase as pregnancy progresses.

## 6.4 Summary

This chapter presented a personalized sleep approach to evaluate sleep quality adaptations of pregnant women during pregnancy and postpartum. The approach was designed and developed for a real human trial on maternity health using the Bayesian RNN as a semi-supervised machine learning algorithm. In this regard, the sleep data at the beginning of the monitoring were exploited to construct sleep models for pregnant women. Then, the models were utilized to investigate the sleep changes in the rest of the pregnancy and the postpartum. The models produced abnormality scores that are indicating the degree of changes in the sleep events during the monitoring.

The performance of the proposed approach was evaluated, in comparison with a baseline method determined sleep adaptations using overall population data of pregnant women in their normal conditions. The proposed patient modeling enabled a personalized decision-making approach in long-term health monitoring, where the variations in an individual's health conditions identified by comparing her data with her own historical data. Therefore, the users who required more care could be recognized correctly. Such personalized decision-making can optimize resource allocation in IoT-based systems according to the user's needs. This optimization leads to improvement in the quality of care in these systems.

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Figures 6.1–6.3 and Tables 6.2 were taken from Paper VI





## Chapter 7

# Conclusion and Future Work

IoT technologies are fundamentally transforming the way healthcare systems operate. Such advancements allow health and well-being services to be offered that are beyond the limits of conventional clinical settings, as individuals are continuously and remotely monitored for preventive care and early intervention. However, this synergy brings new challenges that need to be addressed to ensure the satisfactory performance of such mission-critical health applications. This research investigated and discussed: 1) what the requirements of ubiquitous health monitoring systems are, and 2) how these requirements can be addressed via personalized data analytics approaches.

To pursue **Research Objective I** (i.e., analysis and examination of IoT-based systems in healthcare), this thesis surveyed state-of-the-art IoT-enabled healthcare systems proposed for both in-home and in-hospital settings. Based on this survey, a new perceptible was then introduced into the field by categorizing these healthcare systems into different domains according to the user's requirements and demands (i.e., a user-centered perspective). Home-based applications were investigated indicating the role of IoT-based systems in remote elderly monitoring. Hospital-based applications were also examined to present the trends of IoT systems in hospitals and their benefits for hospitalized patients, nurses, and health providers. In addition, the findings were analyzed to categorize and examine the objectives of IoT-based systems in health monitoring applications. Then, the requirements and technical challenges were discussed, that should be overcome to deliver high quality and effective care to the end-users.

This thesis attained **Research Objective II** (i.e., design and implementation of a personalized computing architecture in IoT-based healthcare systems) by introducing a hierarchical computing architecture for IoT-based system. It tackled the requirements of real-time monitoring systems, providing high-level quality attributes. The core contributions of the proposed architecture were: 1) to partition and execute existing linear and non-linear

machine learning algorithms into 3-layer IoT systems; and 2) to enable a closed-loop management technique to automatically and adaptively re-tune the system's configurations according to the user's condition. The architecture was evaluated via a case study on real-time arrhythmia detection, in which ECG signals were continuously collected. The experiments were carried out on two levels: 1) a binary abnormality detection using a linear SVM method; and 2) a multi-class arrhythmias classification using a CNN method. A full-system implementation was demonstrated, and the proposed architecture was compared with a baseline cloud-based architecture. The results showed that the proposed architecture could improve availability, response time, and bandwidth utilization of the system as well as enhance the accuracy through personalization.

In addition, this thesis achieved **Research Objective III** (i.e., design and implementation of personalized data processing and modeling techniques in IoT-based healthcare systems) by tailoring the benefits of IoT systems to design and customize data analytic approaches. A personalized data fusion approach was proposed to tackle missing data as a prevalent problem in IoT-based system. The approach exploited multiple data resources in IoT-based systems to perform real-time decision-making, despite the occurrence of missing data. The approach was tested via a case study on maternal health monitoring, where 20 pregnant women were remotely and continuously monitored for 7 months. Within the evaluation, a rule-based indicator was considered to translate health data into a health decision. The proposed approach was evaluated in a comparison with existing missing data analysis methods. As a result, the proposed approach improved the system's resilience and achieved a better accuracy than the other methods.

From another perspective, and considering **Research Objective III**, this thesis presented personalized decision-making in long-term health monitoring, leveraging a Bayesian RNN method. The method exploited the historical data of users to track variations and events in their data. The proposed method was tested during the maternal health monitoring, focusing on sleep quality degradation during and after pregnancy. With this intention, and for each individual, a sleep model was created utilizing the person's sleep data from the beginning of the monitoring. Then, the trained model was used to track the trends and events in each woman's sleep data for the rest of the monitoring. The model produced an abnormality score for each sleep event, allowing an explicit representation of sleep quality. For the evaluation, the personalized method was compared with a baseline method that obtained the abnormality level by comparing the data with data from the overall population. The results showed that the personalized method could correctly detect sleep changes during the monitoring. This detection could improve individualized and effective care in IoT-based health monitoring systems.

## 7.1 Future Direction

As mentioned previously, using IoT-based systems for ubiquitous health monitoring is in the early stages. Therefore, there are still various open problems and challenges concerning such monitoring systems and the role of personalized data analytics.

This thesis covered many types of in-home and in-hospital health monitoring studies to achieve a comprehensive perspective of the field. Such studies were diverse in terms of feasibility and practicability. Therefore, one of the open research directions is to perform feasibility studies evaluating such systems in real-life longitudinal health monitoring. These studies should investigate the usability of different sensing, communication, and computing paradigms of the IoT-based systems from both user-centered and application-centered aspects.

We proposed an IoT software architecture to enable personalized resource management. Our work was focused on the configurations of fog and cloud, to optimize bandwidth utilization and data storage with respect to the user's condition. This work can be extended to the perception layer, to apply a personalized energy management. In this regard, different parameters in the data collection process (such as awake/sleep modes and sampling frequency) could be optimized. This optimization could improve the power consumption of the sensors.

In addition, we exploited a semi-supervised machine learning algorithm to extract abnormality in the sleep data of an individual according to her own historical data. This work can be extended by including other health data (i.e., attributes) in the analysis. In this regard, more experiments on the semi-supervised settings should be implemented, and the impact of labeled data on such settings should be investigated. Moreover, the proposed sleep model was evaluated in comparison with a baseline method that was a simple aggregate method. In future work, the proposed method should be compared with other baseline methods, such as unsupervised learning methods.

Most of the longitudinal studies targeting maternal health were merely restricted to subjective measurements (e.g., self-report questionnaire). In this thesis, we conducted a case study on the maternal health of 20 pregnant women, implementing objective data collection. However, the data collection was limited to a wristband due to the feasibility of the 7-month monitoring. This data collection restricted our data analytic techniques and subsequently the investigations in our study.

Therefore, more objective longitudinal studies are needed. Future work could be twofold. First, the studies could be performed via more advanced multi-sensor data collection, where multiple vital signs and contextual data are recorded. PPG, as a non-invasive technique, can be tailored to obtain

various vital signs such as heart rate, respiration rate, and oxygen saturation. Therefore, more comprehensive patient's models could be constructed, leading to more robust decision-making approaches. Second, the longitudinal studies should be carried out for a larger population. In this regard, statistical analysis and machine learning approaches could be exploited to investigate associations between pregnancy-related parameters and both maternal and fetal health problems.

## Chapter 8

# Overview of Original Publications

This chapter presents a brief overview of the original publications included in this thesis.

### 8.1 Paper I: Internet of Things for Remote Elderly Monitoring: A Study from User-Centered Perspective

In this paper, we conduct a comprehensive review of the existing IoT-based systems designed for remote elderly monitoring. In this regard, the systematic search process includes peer-reviewed publications of five digital libraries and research/industrial projects funded from 2009 to 2015 by five research programs. We investigate the existing literature from a user-centered perspective. The major studies are selected and classified according to the requirements of the elderly. We then propose a hierarchical model for the elderly-centered monitoring, investigating the existing approaches based on their objectives. Finally, the paper presents a discussion concerning the current trends and future directions of the IoT-based elderly monitoring systems.

#### Author's contribution

The author is the first author in this publication. He had a major role in the conceptualization and review design. He played the main role in collecting and analysis of the articles. In addition, he contributed to the preparation of the manuscript.

## **8.2 Paper II: The Internet of Things for Basic Nursing Care A Scoping Review**

In this paper, we conduct a survey study on the state-of-the-art IoT-based systems proposed for basic nursing care in hospitals. The review methodology is implemented through a review consisting of scientific papers from eight digital libraries. Considering different criteria for the study, sixty-two papers are chosen. We present abstract information from the selected papers including development type, target patient group, and study type. We then discuss and categorize these papers in seven domains and in four basic nursing care activities. This study presents a broad view of the field, by which the nursing sciences might benefit from a deeper understanding of IoT technologies.

### **Author's contribution**

The author is the second author in this publication; however, he contributed as the first technical author of the computer science team. He had a major role in the collection and analysis of the articles (particularly the technical articles). Moreover, he contributed to the review design and drafting of the manuscript.

## **8.3 Paper III: HiCH: Hierarchical Fog-assisted Computing Architecture for Healthcare IoT**

In this paper, we introduce a novel hierarchical computing architecture for IoT-based health monitoring systems. We customize an existing computing model for the proposed architecture allowing resource management in the system. The proposed architecture enables hierarchical partitioning and execution of machine learning algorithms in IoT-based systems and a closed-loop management technique to adaptively update the configuration of the system according to the user's condition. We evaluate the function and performance of the proposed architecture by demonstrating a full-system implementation for a case study on ubiquitous health monitoring. The monitoring is designed to perform arrhythmia detection for individuals suffering from cardiovascular diseases. In the evaluation, the proposed architecture is compared with a conventional IoT architecture. The results show that the proposed architecture improves the availability, response time, and bandwidth utilization in IoT-based systems.

### **Author's contribution**

The author is the first author in this publication. He had a major role in the design of the proposed hierarchical architecture. Furthermore, he was the major contributor to the implementation of the arrhythmia detection case study and evaluation of the proposed architecture. He contributed to drafting the manuscript.

## **8.4 Paper IV: Empowering Healthcare IoT Systems with Hierarchical Edge-based Deep Learning**

In this paper, which is an extension of Paper III, we investigate the function of the hierarchical computing architecture by employing CNN as a deep learning algorithm in the IoT system. We test the system by implementing a continuous health monitoring system focusing on arrhythmias classification. Our results show that the architecture is capable of fully employing the CNN and displays high-levels of availability and accuracy in IoT-based systems. We also indicate that the response time of the system can be optimized in this architecture by choosing an appropriate gateway device. Moreover, we demonstrate that the accuracy of the classification is improved in the architecture by re-training the classifier using the data collected during the monitoring.

### **Author's contribution**

The author is the first author in this publication. He had a major role in the design of the study, implementation of the arrhythmia detection case study, and evaluation of the proposed hierarchical architecture. He contributed to drafting the manuscript.

## **8.5 Paper V: Missing Data Resilient Decision-making for Healthcare IoT through Personalization: A Case Study on Maternal Health**

In this paper, we propose a personalized missing data resilient decision-making approach to continuously provide health decisions for users despite the occurrence of missing data during the monitoring. The proposed approach leverages different data resources in IoT-based systems to estimate the missing value. The approach employs a multiple imputation method in the system to estimate different values, generate decisions according to

the estimates, and finally pool the decisions into one final decision. The approach is proposed for a real human subject trial on maternal health in which 20 pregnant women were monitored for six months of pregnancy and one month postpartum. We compare the proposed method with four existing methods. Our approach obtains more accurate estimates in both short and large missing windows.

### **Author's contribution**

The author is the first author in this publication. He played the principal role in the design of the study and the proposed system. He was the main contributor to the implementation and evaluation of the missing data analysis methods. In addition, he contributed to the design of the setup and data collection of the maternal health monitoring. He also contributed to drafting the manuscript.

## **8.6 Paper VI: Personalized Maternal Sleep Quality Assessment: An Objective IoT-based Longitudinal Study**

In this paper, we propose an IoT-based monitoring system to perform objective sleep quality assessment during pregnancy and postpartum. We implement a long-term monitoring of 20 pregnant women to remotely collect sleep data for six months of pregnancy and one month postpartum. Sleep data from 13 participants ( $172.15 \pm 33.29$  days of data per person) are included in our sleep analysis. To evaluate the sleep data, our contributions in the analysis include two parts 1) the extraction of eight objective attributes from the sleep data and the observation of their variation during the monitoring; and 2) the proposal of a neural network-based approach to generate a personalized sleep score leveraging the historical data of the users. This score shows an explicit representation of the sleep quality. Our fine-grained objective attributes and the sleep score show that there is a decrease in sleep quality at the end of pregnancy, and this becomes even worse in the postpartum. In addition, we compare the proposed method with an aggregate method as a baseline. We show that our method enables personalized decision-making in the sleep analysis of pregnant women.

### **Author's contribution**

The author is the first author in this publication. He was the major contributor to the design of the study and the proposed system. Moreover,



he contributed to the sleep data analysis. He also contributed to the design of the setup and data collection of the maternal health monitoring. He contributed to drafting the manuscript.



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**Part II**

**Original Publications**



# Paper I

## **Internet of Things for Remote Elderly Monitoring: A Study from User-Centered Perspective**

**Iman Azimi**, Amir M. Rahmani, Pasi Liljeberg, and Hannu Tenhunen  
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## Internet of things for remote elderly monitoring: a study from user-centered perspective

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**Abstract** Improvements in life expectancy achieved by technological advancements in the recent decades have increased the proportion of elderly people. Frailty of old age, susceptibility to diseases, and impairments are inevitable issues that these senior adults need to deal with in daily life. Recently, there has been an increasing demand on developing elderly care services utilizing novel technologies, with the aim of providing independent living. Internet of things (IoT), as an advanced paradigm to connect physical and virtual things for enhanced services, has been introduced that can provide significant improvements in remote elderly monitoring. Several efforts have been recently devoted to address elderly care requirements utilizing IoT-based systems. Nevertheless, there still exists a lack of user-centered study from an all-inclusive perspective for investigating the daily needs of senior adults. In this paper, we study the IoT-enabled systems tackling elderly monitoring to categorize the existing approaches from a new perspective and to introduce a hierarchical model for elderly-centered monitoring. We investigate the existing approaches by considering the elderly

requirements at the center of the attention. In addition, we evaluate the main objectives and trends in IoT-based elderly monitoring systems in order to pave the way for future systems to improve the quality of elderly's life.

**Keywords** Internet of things · Elderly care · Remote elderly monitoring · Healthcare and well-being

### 1 Introduction

Thanks to the developments in the medical science and related technologies, the world life expectancy index has been increased for the last decades, and has been projected to further increase in the future (WHO 2014). Subsequently, the number of elderly people will grow with a rapid rate (see Fig. 1). Senior adults require more attention and care as a minor accident or an insignificant disease may cause irreparable damages (WHO/Europe 2015). It should be also considered that many senior adults may live alone whereas it is necessary to be monitored or assisted by caregivers or medical experts. Therefore, there exists an increasing demand for developing novel technologies to provide efficient remote elderly monitoring services. To this end, various modern disciplines should be utilized to address the elderly requirements considering their limitations in daily life. Internet of things (IoT) as a promising paradigm can provide such essential services for elderly adults (Dohr et al. 2010; Huaxin et al. 2012).

IoT is an advanced technology exploiting various disciplines such as sensor development, data acquisition, communication and networking, data management and data processing, etc. where things (e.g., objects, people) with unique identities are able to connect to a remote server and also to form local networks (Atzori et al. 2010). The

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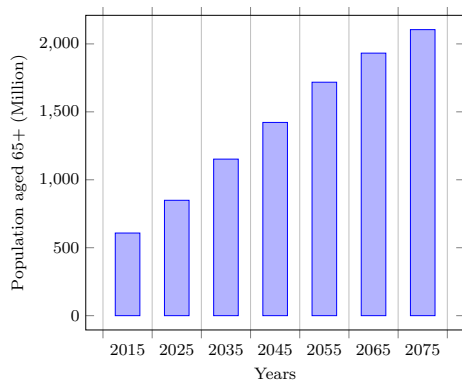
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**Fig. 1** Projection of world population of elderly (65+). Probabilistic population projections by United Nations (2015)

connectivity in IoT-based systems enables objects to exchange and fuse data to achieve a more comprehensive knowledge regarding their functionality as well as properties of the surrounding environments, thus, offering more enhanced, intelligent and efficient services. One of the main features of the IoT technologies is to facilitate improving the quality of life by enabling continuous (i.e., 24/7) remote monitoring systems (Niyato et al. 2009; Ray 2014).

There exist several efforts to utilize IoT-based system for elderly monitoring and care, most of which target only certain aspects of elderly requirements from a limited viewpoint (e.g. health monitoring, safety monitoring, etc.). Considering the significance of remote elderly monitoring and the variety of potential services that such systems can offer, there still exists a lack of a user-centered study. A user-centered design utilizes multiple sources to introduce a system focusing on the capabilities, requirements and abilities of the users (Ritter et al. 2014). Hence, it is essential to consider the existing monitoring systems for senior adults from a user-centered perspective, and discuss deployment challenges of monitoring applications from an all-inclusive top view.

In this paper, we study and classify the existing literature from an elderly-centered perspective to develop a comprehensive mindset on the area and evaluate the future trends. We discuss the current challenges from a different standpoint and present potential services offered by IoT technologies. Our study paves the way for future works in a new perspective to improve the quality of life of elderly people.

The rest of the paper is as follow: in Sect. 2, we present the significance and the motivation of this research. The methodology is described in Sect. 3. A common

architecture of IoT-based systems is discussed in Sect. 4. In Sect. 5, we investigate the existing approaches in the context of remote elderly monitoring from a user-centered viewpoint. In Sect. 6, we classify the presented efforts, summarize their pros and cons, and illustrate the differences. In addition, we discuss the main objectives that IoT-based systems should seek in their implementation. Finally, Sect. 7 concludes the paper.

## 2 Significance and motivation

One of the profound applications of IoT-based remote monitoring systems is for addressing the requirements of elderly people. Frailty of old age, on one hand, makes elderly more susceptible to several diseases (both acute and chronic), impairments (e.g., visual, physical and speech), and weaknesses (e.g., forgetfulness), and on the other hand increases the likelihood of lacking awareness (e.g., computer illiteracy). Therefore, neglecting the importance of elderly care may result in a higher level of elderly's dependency or force them to live in a nursing home. In this context, IoT-based remote elderly monitoring can provide services to address the aforementioned issues, to mitigate the inevitable consequences, and to enable them to live independently.

Several related work in the literature have focused on IoT-based elderly care to provide a variety of monitoring services, however this field is still at infancy as many requirements and problems have not yet been tackled; E.g., the essentials of user-centered system design for elderly monitoring and development of multipurpose systems to monitor a large group of users in order to detect (or predict) patterns or situations that may happen to elderly people such as epidemic diseases. Considering the literature on remote monitoring systems, many shortcomings still exist. Some contributions are too focused in the sense that they only address a single requirement of elderly. For examples, a care system for dementia is presented by Lin et al. (2006), while in-home water sensor-based monitoring and home monitoring systems with Android phones are investigated by Tsukiyama (2015) and Lee et al. (2013), respectively. In addition, there are some studies which investigate the elderly monitoring systems based on a certain aspect (e.g., health-based, activity-based, location-based, etc.). For instance, Memon et al. (2014) provide a survey on healthcare frameworks and platforms of ambient assisted living. Similarly, smart house technologies for elderly and disabled people are investigated by Stefanov et al. (2004). Gokalp and Clarke (2013) study contributions on monitoring of daily living activities of elderly people, while Hamdi et al. (2014) classify elderly related monitoring according to use case (e.g., rehabilitation



telemonitoring and chronic diseases telemonitoring). From a similar viewpoint, Lattanzio et al. (2014) investigates care systems for elderly health and well-being in Italy, which is geographically restricted.

In contrast to the aforementioned contributions, we consider a comprehensive monitoring framework for elderly people to satisfy their daily lives' requirements. The motivation behind our study is to investigate the existing IoT-based elderly monitoring systems from a wider viewpoint by considering the user at the center of the system, to identify the challenges in developing such systems, and to evaluate the current and future trends. The main contributions of this study is as follows:

- Investigating the existing literature from a different angle.
- Developing a comprehensive perspective on the area.
- Evaluating the future trends in IoT-enabled elderly monitoring systems.

### 3 Methodology

In order to fulfill the aims of this study, a systematic search process was conducted through the following sources.

- I. *Digital Libraries* The digital libraries used in this research include IEEEExplore, SpringerLink, ACM DL, Scopus and Pubmed. In this manner, query syntaxes containing “elderly”, “Internet of Things”, “remote monitoring” and Boolean operators (i.e., “OR” and “AND”) were utilized. Out of the obtained results, we selected the related work which: (1) address elderly problems, (2) target remote monitoring, and (3) include or relate to IoT technologies.
- II. *Research Programs* We studied recent projects which have been funded from 2009 to 2015 by research programs and agencies including AAL,<sup>1</sup> FP7,<sup>2</sup> H2020,<sup>3</sup> NCI<sup>4</sup> and ECSEL.<sup>5</sup> The accomplished or ongoing IoT based elderly monitoring projects have been chosen. Then, their associated articles, technical reports, etc. have been studied in order to investigate their proposed procedures, features, and goals. The state-of-the-art projects proposed for elderly monitoring complement this study and can

<sup>1</sup> <http://www.aal-europe.eu>.

<sup>2</sup> <http://cordis.europa.eu/fp7>.

<sup>3</sup> <https://ec.europa.eu/programmes/horizon2020>.

<sup>4</sup> <http://www.cancer.gov>.

<sup>5</sup> <http://www.ecsel-ju.eu>.

help indicating the current and future trends in this field.

### 4 IoT-based system architecture

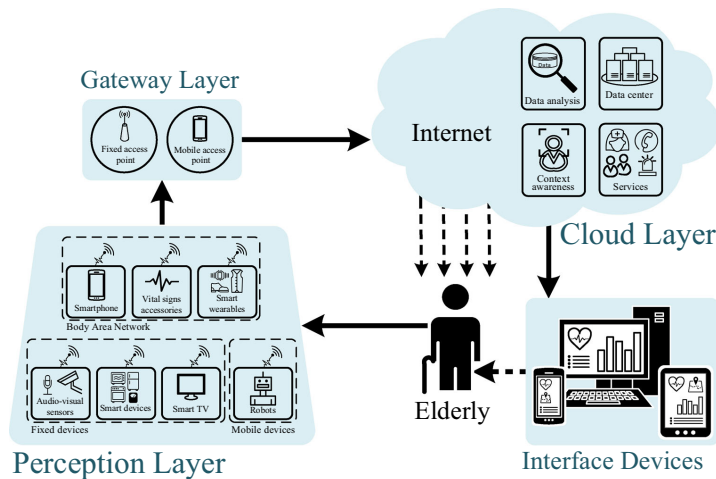
IoT is a rapidly growing paradigm which has the potential to profoundly affect many aspects of human life by connecting objects and people. Based on the features and functionalities of IoT-based system (data collection, transmission, and analysis), the system architecture can be partitioned into 3 layers as proposed by Touati and Tabish (2013). However, architecture of an IoT-enabled system can be redefined with respect to its use cases. As shown in Fig. 2, in our case, to address the requirements of elderly monitoring, the system is defined as follows:

The first layer named as the *perception layer* is the closest tier to the person under monitoring. The main purpose of the perception layer is to collect required data from user and to interplay with the higher layers. As illustrated in Fig. 2, the perception layer can be divided into two categories: body area network (BAN) and fixed/mobile devices in the proximity. BAN which includes on-body and implantable devices can be a network of vital signs accessories (e.g., chest straps, pulse oximeters and blood pressure monitor) or smart wearable devices (e.g., smartwatch, fitness tracker and smart hat) which are in charge of obtaining user's status. Medical parameters including vital signs (e.g., heart rate and respiration rate), blood glucose level, galvanic skin response (GSR), etc. and activity specifications like position, activity level and sleep level are collected using such devices. Fixed context devices are in the second category which are often installed in the home or other public places (e.g., surveillance camera, Smart TV, etc.). Mobile context devices are also used to sense environmental parameters and to response based on the situation. Robots of different kinds can fit in this category.

*Gateway layer* is at the second tier. It receives sensory data from the perception layer via wired or wireless communication protocols (e.g., Bluetooth, 6LoWPAN and Zigbee) and then transmits the data to the Cloud layer for further analysis. In Fig. 2, the layer is divided into two types. The first one is dedicated to fixed access points which are installed in elderly home for indoor data transmission. The second type is mobile access point utilized for outdoor requirements. Smartphone is a typical example of a mobile access point which is capable of implementing data transmission and processing.

The *Cloud* is the third layer. This is a remote layer located in the data center. As depicted in Fig. 2, the Cloud layer consists of various sections. Heterogeneous incoming

**Fig. 2** A multi-layer IoT-based elderly monitoring system architecture



data is stored in data centers to be analysed by utilising high processing power at the Cloud. The data analysis includes reasoning (Russell and Norvig 2013), machine learning algorithms (Murphy 2012), pattern recognition methods (Bishop 2006), etc. Based on the obtained results, decisions and responses are made to efficiently react with respect to the elderly requirements. These back-end applications can provide behavioral changes detection such as Mild Cognitive Impairment (MCI) detection in elderly (Akl et al. 2015) as well as predicting chronic diseases, e.g. blood glucose concentration prediction for a person with diabetes (Zecchin et al. 2014) and acute diseases prediction including cardiac arrest prediction (Liu et al. 2012). Furthermore, various applications and services such as mobile user interface can be offered to transmit the results to end-users, e.g. monitored person, caregivers and medical experts.

System security plays also an important role in IoT based systems especially in the remote elderly monitoring systems where senior adults' privacy and trust should be preserved. According to the three tiers architecture of the system, the potential security issues can be considered in three parts (Yang et al. 2012). The first part includes the perception layer in which the sensor nodes without a security policy may be attacked. The second part is related to the Gateway layer which has a strategic bridging position of delivering the data to the cloud or sending commands to sensor nodes. Many adversaries target these Internet-connected gateways to attack. At the gateways, unauthorized access or damage to the data transmission causes critical security problems for the system. Finally, the third part targets the Cloud issues.

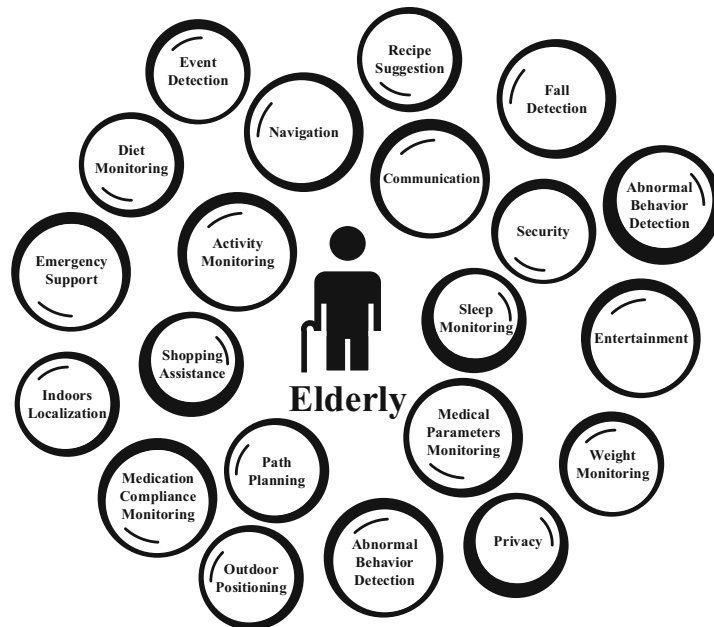
The Cloud including data centers contains all of the history and collected data of the monitored people and their environments, so a data breach may cause irreversible damages for the individuals and the system. Therefore, satisfying security requirements such as data authenticity, data confidentiality and access control are essentials in IoT-based systems (Sicari et al. 2015). In this regard, various models or schemes have been introduced to ensure security in the IoT-based systems; e.g., Vucinic et al. (2015) propose a model (OSCAR) for end-to-end security in the IoT systems, Moosavi et al. (2016) also present an end-to-end security scheme for mobility enabled healthcare IoT systems and Neisse et al. (2015) offer a model to provide security for data protection in IoT systems.

## 5 Elderly-centered IoT-based remote monitoring

Taking into account the projected high rate of elderly population growth (see Fig. 1) in the near future, it is essential to dedicate significant efforts to exploit advanced concepts and technologies such as IoT in the elderly care. A variety of solutions have been provided to address the elderly needs by compensating the deficiency or mitigating the inevitable consequences. Figure 3 demonstrates some of these existing solutions and services. With this intention, many small, medium, and large projects have also been launched to tackle the elderly requirements with different objectives.

We investigate major IoT-based applications and services that have been thus far introduced for remote elderly

**Fig. 3** Variety of applications and services proposed for remote elderly monitoring



monitoring. Due to the importance of monitoring in this context, we aim at studying such efforts from a different angle by considering elderly at the center of attention and classify different approaches with respect to their properties and benefits in daily life. In this manner, we categorise the applications and services of the approaches into five different sections: (1) health monitoring, (2) nutrition monitoring, (3) safety monitoring, (4) localization and navigation, and (5) social network, each of which is essential and includes some aspects of indoor and outdoor requirements.

Figure 4 demonstrates a general view of elderly daily life, IoT-based system architecture, and the advantages provided by the IoT technologies in different situations. The system offers remote monitoring applications as well as providing services such as reports (daily, monthly, etc.), suggestions and early alerts. It also shares the elderly information to the third party agents (i.e., caregivers, medical experts and emergency units), so they can intervene in case of emergency, suggest medical advices and provide supports. Moreover, the system is able to receive feedback from the third party agents in order to offer more personalization for the user and to improve the performance (e.g., system's sensitivity and specificity). In such systems, various issues such as data integrity, data

authenticity and data confidentiality should be considered (Jara et al. 2013; Henze et al. 2016).

In the following, we study IoT related platforms and approaches by classifying them into five categories. It should be noted that some of these solutions lie in more than one category. This is also highlighted in Table 1. In addition, since various aspects of an approach may be introduced in different papers, a summary of which is provided in the related category and the associated papers are cited in the explanation. For instance, SAAPHO project along with its main associated publications (Rivero-Espinosa et al. 2013; Rafael-Palou et al. 2015; Ahmed et al. 2015) are introduced and explained in Sect. 5.1.

### 5.1 Health monitoring

According to the increased frailty and susceptibility to various diseases (e.g., acute and chronic diseases) in old age, health monitoring becomes the most important part of elderly remote monitoring. Remote health monitoring not only improves the quality of life of elderly people, and detects and notifies caregivers in the case of emergency, but also reduces nursing and hospital stays and subsequently healthcare costs. According to a report by the Agency for Healthcare Research and Quality

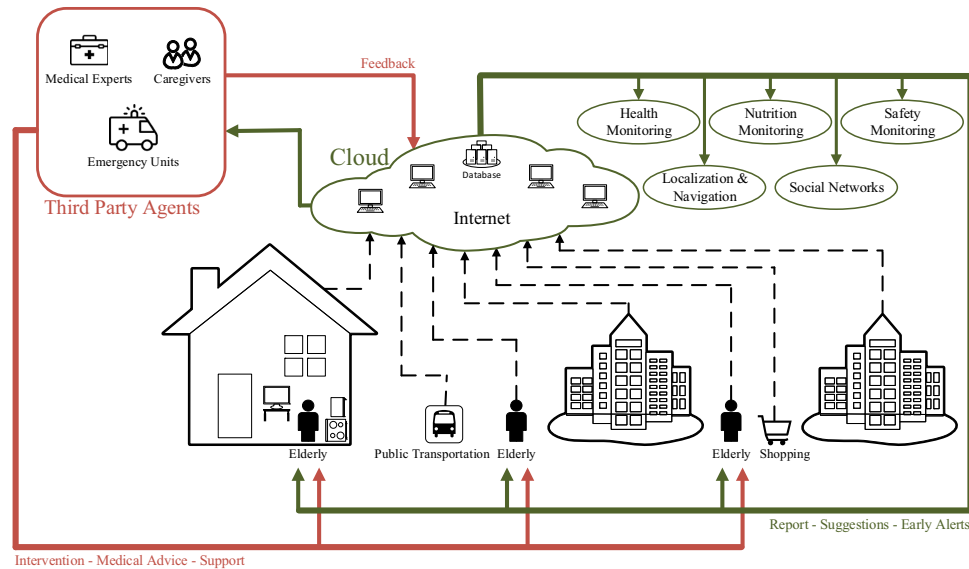


Fig. 4 An all-inclusive view of IoT-based remote elderly monitoring systems

(AHRQ) (Pfundner et al. 2013), in 2011, more than one third of aggregate hospital costs and stays in the United States were spent for elderly people (see Fig. 5); Thus, it is essential to improve the care services and to reduce the hospital costs and stays of elderly people by providing remote health monitoring services at home. Furthermore, a significant number of senior citizens in the future may encounter with limited number of care and supportive services due to the reduction of potential supportive ratio  $\left(\frac{\text{Age}25-64}{\text{Age}65+}\right)$  in the world (see Fig. 6) and the growing burden of aging associated diseases (and subsequently related costs) (WHO 2011).

We chose main health monitoring services with respect to requirements, diseases, and impairments of elderly people. As a significant part of a health monitoring system, the vital signs are collected and monitored in order to indicate a person's medical status. Early attempts on determining the medical status of a patient were implemented by obtaining four basic medical vital signs (i.e., temperature, pulse rate, respiratory rate and blood pressure) (Glaeser and Thomas Jr. 1975). Afterwards, more parameters were also added to the patient's condition evaluations. In 1997, a score system entitled Early Warning Score System (EWS) was introduced by Morgan et al. (1997). In the proposed EWS system, parameters such as respiration rate, heart rate, oxygen saturation and also level

of consciousness are collected in order to predict patient deterioration in hospitals. In this regard, according to the possible serious medical condition that some elderly people might have, personalized EWS system is proposed to collect vital signs and to calculate the EWS scores in various conditions remotely (Anzanpour et al. 2015; Azimi et al. 2016). Moreover, in addition to vital signs, other medical parameters such as glucose and urine amount can be included to have a more comprehensive analysis.

In the same fashion, different approaches have been recently proposed to address remote health monitoring for elderly people. In SAAPHO project (Rivero-Espinosa et al. 2013), a system with an Android user-friendly platform is introduced to provide various aspects of elderly monitoring including health monitoring. It contains medical and activity monitoring parameters such as physical activity, blood pressure, glucose, medication compliance, pulse monitoring and weight. In this system, the data is transmitted via HTTPS and SOAP web services from the sensor layer to the Cloud. Then, after data analysis, the obtained results are transferred to the interface devices. Therefore, caregivers or medical experts can monitor the users by getting notified about emergency situations, historical summary (Rafael-Palou et al. 2015) and generated recommendations based on the recorded history data (Ahmed et al. 2015). Similarly, MOBISERV (Nani et al.

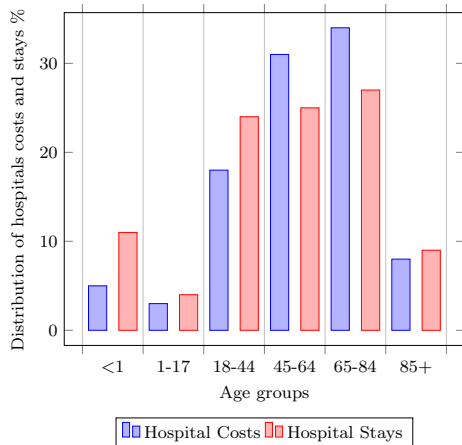
**Table 1** A comparison among several approaches providing remote elderly monitoring

Project's name	Time period (years)	Health monitoring	Nutrition monitoring	Safety monitoring	Localization and Navigation	Social network	Other features
ALFRED	2013–2016	✓	–	–	–	✓	Physical and cognitive impairments prevention
ALICE	2010–2012	–	–	–	✓	–	Eligible for who are suffering from visual impairments
ASSAM	2012–2015	–	–	–	✓	–	Eligible for who are suffering from physical impairments
ASSISTANT	2012–2015	–	–	✓	✓	–	Mistake detection and classification
CaMeLi	2013–2015	–	–	✓	–	✓	Emergency situation notification Human-like virtual system Emergency situation notification Activity reminder
ChefMyself	2013–2015	✓	✓	–	–	✓	Includes a recipe library Shopping assistance
CONFIDENCE	2008–2011	–	–	✓	✓	–	Activities and postures recognition
DIET4Elders	2013–2016	✓	✓	–	–	✓	Daily activity monitoring and advice
EDLAH	2013–2015	–	✓	–	–	✓	Object location indicator Activity reminder
ELF@Home	2013–2016	✓	–	–	–	–	Elderly fitness monitoring
FEARLESS	2011–2014	–	–	✓	–	–	Emergency situation notification
GeTVivid	2013–2016	–	–	–	–	✓	A TV based system Public services (e.g. medical and shopping assistance, etc.) Activity reminder
HEREiAM	2013–2016	✓	–	✓	–	✓	A TV based system
Mobiserv	2009–2013	✓	✓	✓	–	✓	A personal robotic based system Nutrition habits monitoring
NITICS	2013–2015	✓	–	✓	✓	–	Emergency situation notification Object location indicator
SAAPHO	2011–2014	✓	–	✓	–	–	Generate advices w.r.t the recorded data Emergency situation notification
vAssist	2011–2014	✓	–	–	–	✓	Eligible for who are suffering from physical impairments Eligible for who have no computer literacy
WIISEL	2011–2015	✓	–	✓	–	–	Gait analysis Early identification of mobility

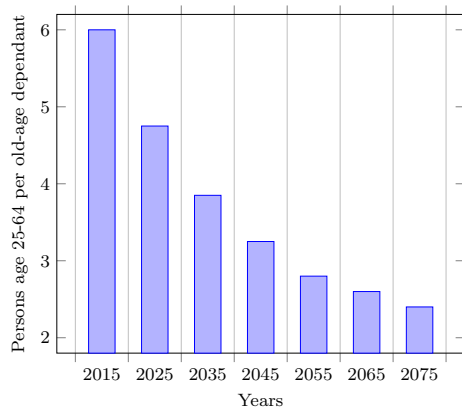
2010) as a multipurpose project, propose a system consists of a companion robot and wearable textiles (Faetti and Paradiso 2012). In this system, the elderly healthcare is addressed by monitoring medical parameters (e.g., ECG and vital signs) remotely.

Daily activity is another parameter representing the health status of elderly. The activities include physical activity level, the act of eating (i.e., number of meals per day and duration), sleeping, etc. For this purpose, several contributions have been proposed utilizing different methods and sensory data in order to offer activity

monitoring for elderly people. Kasteren et al. (2010) present a system (within the CARE project) including wireless sensors and a recognition models to track and recognize activity level of elderly people. Moreover, Charlon et al. (2013) propose a telemetry system utilized in a combined trilateration method using a smart hat and smart shoes to accurately track indoor elderly activities. In the same category, a textile capacitive neckband is also proposed by Cheng et al. (2013) to detect daily activities such as eating and sleeping by monitoring head and neck movements. In addition, using vision sensors, Xiang et al.



**Fig. 5** Distribution of hospital costs and stays by age in the United States, 2011 provided by Agency for Healthcare Research and Quality (AHRQ) (Pfundner et al. 2013)



**Fig. 6** Projection of World potential supportive ratio  $\left(\frac{Age_{25-64}}{Age_{65+}}\right)$ . Probabilistic population projections by United Nations (2015)

(2015) present an omni-directional vision sensor based system to track individuals, to recognize the posture, and to analyze the behavior.

Likewise, by considering the benefits of self-care, projects such as ELF@Home (Carus et al. 2014) introduce a system to monitor elderly fitness. In this project, the system offers real-time services to track daily activity level (by wearable physical activity sensor along with a computer vision system) and health status (using bio-sensors).

A personalized fitness program is then proposed without needing a direct human supervision where the improvements are applied based on sensors' feedback.

Acceptance of a new technology is often a challenge, in particular when elderly are the target users of the system. This restricted some health monitoring approaches to use conventional devices (e.g., TV) for providing more user friendly services for the senior adults. In this regard, a digital TV based remote health monitoring service is proposed by Spinsante and Gambi (2012) using several wireless medical devices (e.g., oximeter, breathing tester and glycaemia meter). Similarly, HEREiAM project (Macis et al. 2014) demonstrates a TV based system in order to offer a wider assistance and support for elderly people. The project offers a variety of services using a TV set at home (HEREiAM 2015) to address remote health-care technology acceptance along with other issues such as security and social communication.

## 5.2 Nutrition monitoring

Malnutrition due to deficiency (i.e., under-nutrition), excess (i.e., over-nutrition) or lack of proper nutrition is a common problem in aging which can be controlled. The prevalence rate of malnutrition is higher among elderly people (Stratton et al. 2003; Hickson 2006). Negligence of malnutrition in a time period can make elderly people susceptible to different diseases such as cardiovascular and cerebrovascular diseases, osteoporosis, and diabetes (WHO 2016a). Therefore, it is essential to consider nutrition monitoring, particularly weight and diet monitoring, along with health monitoring in IoT-based remote monitoring systems to enhance health and well-being of elderly people.

In this regard, different approaches and systems have been hitherto proposed. ChefMyself is a nutrition-related monitoring which introduces a system to support food related monitoring for elderly people (Lattanzio et al. 2014). Using a Cloud based connection, it offers remote nutrition monitoring that includes weight monitoring (by wireless scales), diet monitoring, recipe library, and shopping and cooking assistance for elderly people. It also provides social network accesses (see Sect. 5.5) to motivate elderly to have a better social life.

Similarly, to prevent malnutrition for old people, another approach called DIET4Elders (Sanchez et al. 2013) demonstrates a system (hardware and software) to monitor, advice and provide services for daily activities related to dining pattern of elderly people. Their proposed system consists of three layers (Sanchez et al. 2013): (1) Monitoring Layer to capture raw data from daily activities, (2) Analysis and Assessment Layer to extract information (Chifu et al., 2014) and to extract knowledge

about the daily self-feeding, and (3) Support Service Layer to provide complementary knowledge (including communications) from medical experts and caregivers.

Another project entitled EDLAH (EDLAH 2015) also addresses elderly nutrition monitoring by introducing complementary system brought to users' tablets. In this manner, the application is connected to other devices (e.g., weighing scale) to have a more inclusive monitoring. Moreover, in the same package, other services are also offered (Borsella et al. 2015) such as medicine reminder, object location indicator (Ionescu et al. 2014), and social networks.

To achieve a multipurpose remote monitoring, a wearable IoT based device called eButton (Sun et al. 2014; Bai et al. 2012) has been designed for people with special needs such as elderly. The eButton device provides diet monitoring using a visual sensor installed on the user's chest. The food volume is also estimated from the images based on prior models of foods shapes. The obtained data coupled with supplementary data (e.g., food information) shows daily nutrition and calories of the user. Furthermore, the device also offers services for physical activity monitoring to estimate issues such as sedentary events and daily caloric expenditure.

Unlike the discussed application-oriented approaches, MOBISERV as also introduced in Sect. 5.1, proposes a personal robotic system along with wearable and environment sensors for remote monitoring. The system is designed to address nutrition and health services of elderly people by detecting elderly emotions and activities (Maronidis et al. 2010, 2011; Iosifidis et al. 2013). Monitoring consumed meals and water are instances of the nutrition habits monitoring proposed in this system (Zoidi et al. 2011; Marami et al. 2011; Iosifidis et al. 2012).

### 5.3 Safety monitoring

Security is one of the major issues in the daily life of elderly people. Ageing causes impairments, frailty and forgetfulness, so to live independently, safety monitoring becomes important. On the other hand, a real-time monitoring system capable of detecting harmful situations can provide a feeling of safety for the old users together with awareness of their status for their relatives who might not be in the vicinity. In this regard, several methods and projects have been proposed to address remote safety monitoring of elderly people. The major ones are discussed in the following to covering different aspects of elderly monitoring in daily activities.

As a result of diseases or limits caused by aging and visual and physical impairments, elderly people have a high risk to fall which might cause fatal injuries and even death, with a higher probability than younger adults (WHO

2016b). To alleviate such consequences, dedicated techniques have been proposed to perform fall detection. Based on the definitions given by Igual et al. (2013), fall detection methods can be divided into two categories: wearable sensors based and context-aware systems based. In the sensory level, wearable sensors separated into two groups as smartphones and miniature sensors mounted on a band or cloth. Wearable sensors provide more comfortable user experience for some users rather than being continuously recorded by cameras in the context-aware systems. Smartphone and sensor based fall detection methods utilize the sensors such as 3D accelerometer, gyroscope and magnetometer to determine the sudden position and orientation changes of a user's conditions, analyse the data and implement further processes (e.g., send notifications) when a fall is detected. Some attempts to propose smartphone based methods can be found in Fang et al. (2012), Sposaro and Tyson (2009) and Mellone et al. (2012) while Pierleoni et al. (2015), Cheng (2014) and Odumbaku et al. (2015) are efforts to present wearable sensors based methods. In the same fashion, CONFIDENCE project (Kaluza et al. 2014) introduces several methods for fall detection, activities recognition and postures recognition (Gjoreski et al. 2011; Lustrek and Kaluza 2009; Kozina et al. 2011) using wearable sensors placed on wrists, chest and ankle of the user. However, another approach entitled as WIISEL (WIISEL 2015) offers a similar system for detecting falls in addition to gait analysing using a wireless insole sensor (Rosa et al. 2015).

On the other hand, context-aware systems are developed to detect falls utilizing visual sensors. Compared with wearable sensors, there are limitations using context-aware systems such as spatial coverage of installed cameras or uncomfotability for some senior adults when they feel being watched all the time. However, context-aware systems also provide certain advantages for the monitored person, such as eliminating the need for wearing the sensor all the time and avoiding the anxiety for forgetting to carry the sensors. In this regard, two main fall detection projects Bian et al. (2015) and Juang and Wu (2015) have been proposed to accomplish the fall detection using a depth camera and a robot vision system, respectively. Furthermore, as an comprehensive elderly monitoring approach using visual sensors, FEARLESS project aims at monitoring elderly people without any wearable sensors (Planinc et al. 2011). In their system, elderly people are monitored continuously by collecting captured data from 3D depth sensor (e.g., Kinect), cameras and microphones, and transferring the data to a computing system (Planinc and Kampel 2012a). In addition, a robust fall detection is proposed to detect the individuals, and their motions, using a combination of different techniques (Planinc and Kampel 2011, 2012b). In this system, when an emergency accident

(e.g., fall) happens, the system transmits the data to the server, and after analysing the data, proper notifications and results are provided via interface devices (e.g., caregivers/medical experts smartphones) (Berndt et al. 2012).

FEARLESS project also introduces a system to investigate behavior changes of patients for detecting unusual activities (e.g., mobility decrease, depression, etc.). Activities in certain places in user's home are monitored to detect the changes in their frequency and duration (Berndt et al. 2012). Subsequently, a comparison on the activity histograms of the collected data is provided by which the system detects abnormal behaviors (Planinc and Kampel 2014). Similarly, NITICS approach (NITICS 2015) presents a localization based system to track the location (Badawika and Kolakowski 2014) and daily activities of the user using portable body sensors along with cameras. The system is designed to distinguish abnormal behaviour (i.e., lack of activities and erratic behavior) and to inform caregivers in case of emergency (Rusu et al. 2015).

The aforementioned approaches (i.e., FEARLESS and SAAPHO) also offer some other services such as environmental accident detection presented in Berndt et al. (2012) and Domenech et al. (2013). Supplementary services are specified to focus on distinguishing the incidence of accidents such as fire, smoke, CO presence and gas leakage.

#### 5.4 Localization and navigation

Mazeophobia (fear of being lost) in unfamiliar environments, reduction of physical and cognitive capabilities, and the risk of confronting odd places without any aid from other people force elderly people to spend most of the time at home. Staying at home for a long time makes elderly people susceptible to be inactive, to lose social life, and to get depressed. Therefore, the significance of remote localization and navigation has motivated the researchers in both academia and industry to provide services for elderly people to feel safe in different environments, and to enable them to have their outdoor activities (e.g., shopping, traveling, etc.). In this regard, various IoT-based approaches have been proposed to address the aforementioned real-life issues and to mitigate their associated inevitable difficulties.

In order to provide assistance for elderly people in outdoor environments, ASSAM project proposes a system to be installed on different mobility platforms (e.g., walker, wheelchair, and tricycle). The assistance system features obstacle recognition, navigational and cognitive assistance and alerts to call center (caregiver) in case of emergency (Krieg-Brückner et al. 2012). The platform provides old adults suffering physical impairments with an automated driving service to a certain location without any

obstacle collision (Mandel and Birbach 2013). An emergency situation system is also demonstrated in this project to notify others along with on-line monitoring services using an on-board camera and an on-line navigational assistance.

Additionally, based on sensory data and maps, the ASSISTANT system is introduced for individuals (particularly senior adults) to navigate and to apply remedial approaches whether an error or mistake occurs. To provide the solution, an application for smartphones was designed (Carmien and Obach 2013; Barham 2013). The application uses the sensory data obtained from phone sensors (e.g., accelerometer and gyroscope) and server data (e.g., routing information from the local public transportation or Open Government Data) via Internet to perform the related analysis (e.g., error detection and classification) locally (i.e., in the smartphone) or remotely (i.e., in the server) (Kalian and Kainz 2013). Besides, the sensitivity and response of the application in case of errors are defined with respect to the user capabilities and requirements (Carmien and Obach 2013).

Providing assistance for elderly people who are suffering from visual impairments is of high importance. For this purpose, a wireless system connected to a local or remote computing unit is proposed in ALICE project. Utilizing a smartphone mounted on the chest of users, the system provides a data fusion of sensory data (i.e., image, sound, positioning, orientation and inclination) for planning and anticipating events (Tapu et al. 2014). The system can robustly detect and classify static and dynamic obstacles without needing prior information (Tapu et al. 2013). Moreover, the project has been extended by introducing methods for object recognition (e.g., crossings, traffic light, etc.) and urban building recognition (Boujelbane et al. 2014; Said et al. 2014).

In addition to the outdoor localization and navigation, some solutions have been proposed to remotely detect indoor location of elderly people. Such techniques enables monitoring activity level of elderly people, recognizing their daily habits, and analyzing their life style and well-being. As an example of indoor localization methods, CONFIDENCE project proposes localization approaches for detecting abnormal activities (Brugger et al. 2010; Zamora-Cadenas et al. 2010). Furthermore, as a supplementary service, some projects present methods for object localization for lost items (e.g., key, eye-glass, cell phone) due to forgetfulness of elderly people. For instance, EDLAH project demonstrate a Bluetooth based method to track and find objects within a house perimeter (Ionescu et al. 2014). Similarly, NITICS project presents an assertive service to locate an object with an appropriate accuracy for indoors measurements (Badawika and Kolakowski 2014).



### 5.5 Social networks

Promoting social life for senior citizens who may live alone is essential. Living alone might lead elderly people to become isolated and having inadequate interaction with other people (e.g., family members, friends, etc.). This subsequently may cause mental problems such as depression and social anxiety. Therefore, preparing social networks to improve the social life for elderly people is as vital as other discussed services. In this regard, a number of social networks utilizing different methods and interaction devices have been proposed for elderly people under different scenarios.

Specific home care and communication services are offered by vAssist project (Caon et al. 2011) for old people who have either movement restrictions or computer illiteracy. They have developed a simplified interface using multilingual natural speech interactions provided by wearable and fixed devices (e.g., smartphones, fall detection systems) for communication applications along with remote medical monitoring (Sansen et al. 2014). The proposed integrated system of natural speech interaction consists of speech recognition, natural language understanding and output generation (i.e., text or audio) (Milhorat et al. 2013, 2014). Thanks to these features, the system can also be utilized for disabled people suffering from physical or visual impairments. Moreover, taking into account the care of solitude elderly people, a virtual assistive companion was suggested by CaMeLi Project (Tsiourti et al. 2014). The proposed platform acquires user behaviour and environment data, analyses them and responds properly with respect to the conditions, thus trying to provide an intelligent system capable of simulating human interactions and conversations. It also offers notifications (e.g., take medicine, do exercises, and eat meals) and safety (e.g., by detecting emergency situation and informing caregivers).

Similarly, ALFRED project (ALFRED 2015) introduces the idea of interactive assistant to enable elderly people to live independently and be active in social life. Using a voice-driven interaction, elderly people are enabled to communicate by asking questions or receiving suggestions based on their requirements and interests (OpenPR 2015). As a complementary service, the system also offers health monitoring (see Sect. 5.1) by tracking users' vital signs with the aim of enhancing physical and cognitive conditions. This is realized by utilizing games and quests provided via a physical and cognitive impairments prevention unit (Hardy et al. 2015).

GeTVivid is another project (GeTVivid 2015) which introduces in a platform of connected TV devices based on the HbbTV standard to provide supports for elderly people suffering from impairments. The system, which includes a

connected TV (TVX2015-Workshop 2015) and applications in smartphones/tablets, offers a social network for communications and social networking (e.g., with caregivers and other old adults) as well as a number of public services such as medical assistance, shopping assistance, and Meals on Wheels. It also includes a reminder for daily activities (e.g., take medicine) (Moser et al. 2015).

## 6 Discussion

As discussed, many accomplished or ongoing elderly monitoring projects have been introduced so far, using various IoT related platforms and methods to implement the services for elderly care. They target several demands of elderly people over their daily life. To classify these efforts, summarize their pros and cons, and illustrate the differences, a comprehensive comparison on the specifications of the discussed projects is given in Table 1.

As can be observed from the table, some of these projects have provided software applications along with embedded devices to deeply tackle a narrow set of elderly requirements. Two proper examples are (1) a user-friendly social network for elderly suffering from impairments by GeTVivid project, and (2) fitness monitoring for improving elderly health by ELF@Home project. Moreover, some projects tackle a single issue using different methods. For instance, as mentioned in Sect. 5.3, fall detection is considered in both FEARLESS and WIISEL projects; However, FEARLESS utilizes camera based methods, while WIISEL is based on wireless wearable sensors. On the other hand, some projects target wider systems and services to address more than one aspect of elderly demands, however they are still at early stages. ChefMyself approach includes health monitoring, nutrition monitoring as well as providing social networks for elderly people. Correspondingly, Mobiserv project covers indoor services (e.g., health monitoring, nutrition monitoring, safety monitoring and social network) utilizing a smart robot.

In addition to the discussed ongoing or recently developed services and products, there exist various IoT-based products which are already available in the market. For instance, various Internet- and Cloud-connected fitness trackers (e.g., Jawbone UP,<sup>6</sup> FitBit,<sup>7</sup> etc.) are in the market which can be utilized for elderly people to track their daily activities and vital signs. There are also available tracking devices for senior adults (e.g. Mindme,<sup>8</sup> SafeLink,<sup>9</sup> etc.) as well as emergency response systems (e.g., MobileHelp<sup>10</sup>)

<sup>6</sup> <https://jawbone.com/up>.

<sup>7</sup> <https://www.fitbit.com>.

<sup>8</sup> <http://www.mindme.care>.

<sup>9</sup> <http://safelinkgps.com>.

<sup>10</sup> <https://www.mobilehelp.com>.

in the market. Medication management systems (e.g., TabSafe<sup>11</sup>) can be also added to this list which help managing medications 24/7. On the other hand, the current existing solutions in the market have still many shortcomings. Some of these devices are not miniaturized, lightweight, low-power, user-friendly, and convenient enough for elderly to wear 24/7. Inaccurate results and false alarms are also issues diminishing the trust of users and caregivers.

In this section, we investigate the issues in IoT-based remote elderly monitoring in a deeper level to pave the way for more efficient systems in future. Nowadays amalgamation of IoT-based systems and big data (Laney 2001; Beyer 2015) analytics enables systems to offer deeper and wider range of services and applications. Therefore, the essential demands of elderly people in their life can be more efficiently addressed in a comprehensive remote monitoring system. With this in mind, we represent a hierarchical model of the elderly-centered monitoring system in 4 tiers in Fig 7. Starting from the lowest level, the first tier entitled as *Application Layer* includes the final applications proposed to tackle the elderly requirements (e.g., activity level monitoring, fall detection, etc.). This layer is discussed in Sect. 5 in details. The second tier is *Domain Layer* including five major monitoring service categories. The applications indicated in the first tier are subsets of these 5 domains. The third tier is defined as *Objective Layer* in order to present and classify high-level challenges/objectives in remote elderly monitoring. Finally, the fourth tier is the *System Layer* which points to a comprehensive elderly-centered monitoring system covering all the divisions and aspects.

In the following, we discuss the objective layer, related challenges and viable solutions for elderly-centered monitoring. As illustrated in Fig. 7, the objective layer is divided into 4 different classes, each of which may partially cover and overlap the domains represented in the previous tier. The first objective is defined to consider an extensive system for addressing the main requirements of elderly. More precisely, it reflects the demand for full-fledged systems in terms of number and type of utilized sensors to monitor vital signs along with environmental and activity related signals. The second objective indicates the issues related to the long-term monitoring of elderly people. Taking into account the back-up systems in case of emergencies is specified in the third class. Last but not least, the fourth class addresses the personalization issues in elderly monitoring systems. Consequently, considering these objectives enables development of a comprehensive elderly-centered monitoring system shown as system layer in Fig 7.

<sup>11</sup> <http://www.tabsafe.com>.

## 6.1 Extensive monitoring

As discussed, all the existing or under-development elderly monitoring systems focus on a subset of aspects of elderly requirements in their everyday life. However, from a user point of view, an extensive monitoring is required to support different applications and services comprehensively. In other words, there is a demand for an all-inclusive monitoring in order to improve the quality of elderly people's life considering a variety of aspects (e.g., addressing the health and well-being requirements, improving the independent living, and enhancing the security). Such a system needs to monitor indoor and outdoor activities of elderly people and to suggest related services in real-time. Thanks to advanced technologies such as IoT-based systems and big data analytics, developing such a system is nowadays feasible.

An extensive IoT-based elderly monitoring system can potentially integrate many objects related to elderly to obtain a comprehensive knowledge of elderly conditions. Considering the issues such as scalability and availability (Mukherjee et al. 2012), it is possible to implement big data analytics to handle a huge volume of incoming heterogeneous data (e.g., health data) and extract useful information (Andreu-Perez et al. 2015). Furthermore, the analysis can be carried out not only using incoming sensory data, but also utilizing history data (e.g., medical records), and complementary data (e.g., maps, public transportation data, shopping info, and weather forecast) to provide more comprehensive services.

The proposed system also needs to be convenient and user-friendly. Elderly people may have different kind of impairments or be forgetful in many situations, therefore, the design process should take these aspects into account. Moreover, attaching a large number of sensors to the body of a user is not appropriate in practical long-term cases if they are not convenient to be deployed. On the other hand, as proposed by some of the discussed approaches, required data can sometimes be collected non-invasively using other devices installed at home or other places. As an example, the elderly status recognition (e.g., detecting fall, unconsciousness, low physical activity, etc.) can be performed using surveillance cameras and computer vision techniques. In addition, several in-home services can be offered via smart home applications and devices (e.g., smart TV, smart stove, etc.).

## 6.2 Long-term monitoring

Long-term monitoring is another challenge of remote elderly monitoring systems. The system should potentially provide long-term services for many years. Impairments and chronic diseases can be properly addressed only by long-term monitoring. As an example, types of diabetes

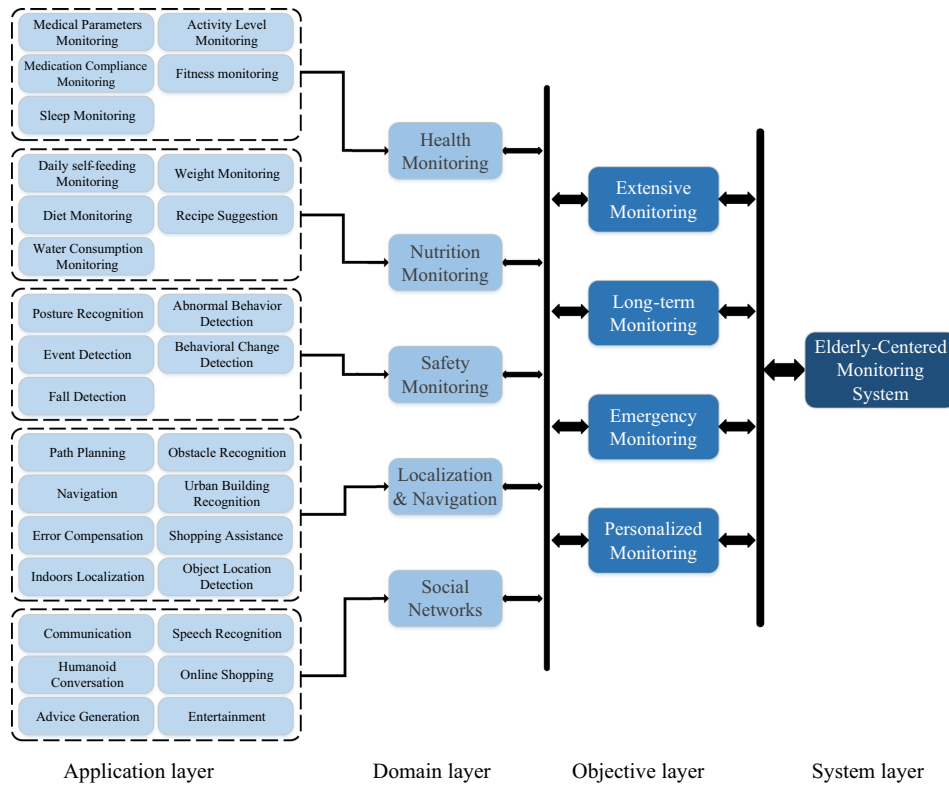


Fig. 7 Hierarchical model of the elderly-centered monitoring system

should be monitored for the whole life span. Thus, lifetime, minimally-invasiveness, and battery-life of sensor devices for a long-term service should be considered. Using compact and limited number of wearable sensors in daily activities as well as utilizing smart devices in the environment can be a proper solutions for IoT-based system in long-term monitoring.

Using long-term monitoring for elderly, the system can analyze the daily habits of the users for a long period in a deeper level. Many physical and mental diseases manifest only via long-term monitoring of habits and behavior of the user. Collecting and analyzing incoming big data in a long period from a user’s daily life including physical activity, eating, sleeping and social life can assist the system to extract valuable knowledge. This knowledge provides a reliable understanding of user’s life style to mitigate improper activities (e.g. low physical activity, insufficient sleep and malnutrition) and enables the medical experts to

perform collective analysis (e.g., analysing prevalent behavior and epidemic diseases). Furthermore, such long-term knowledge may contain changes in habits that can be considered for medical analysis. Various mental illnesses (e.g., depression and anxiety) might be detected or even predicted by monitoring changes in habit in long-time.

### 6.3 Emergency monitoring

Another challenge in elderly monitoring systems is the emergency detection with a low latency and rapid back up supports. The likelihood of accidents such as medical accidents (e.g., stroke and heart attack) and environmental accident (e.g., fall detection, being lost) are higher for elderly adults. Therefore, a comprehensive remote elderly monitoring need to detect emergency situations and react accordingly (i.e., notifying caregivers or medical experts to mitigate the consequences).

In this regard, new concepts such as smart gateways (Rahmani et al. 2015) can be utilized to address the emergency detection issues. The concept of extending the Cloud computing paradigm named as Fog computing closer to the user location has been proposed by Bonomi et al. (2014). In this manner, due to the additional (local) computational power, networking, and online data analysis of the streaming sensory data, the latency of the system is reduced. Moreover, it improves the system reliability in case of unavailability of Internet connection.

#### 6.4 Personalized monitoring

Personalized monitoring is one of the essential objective which IoT-based elderly monitoring systems should consider in a comprehensive monitoring process. In general-purpose elderly monitoring systems, several presumptions are specified for the system based on the general requirements and conditions of users. These presumptions result in inefficiencies in long-term elderly monitoring. Therefore, techniques to provide adaptivity and customization (i.e., personalization) are of utmost significance.

Self-awareness concept (Agarwal et al. 2009) and big data analytics can be integrated to the IoT-based systems in order to provide a personalized monitoring. On one hand, big data analytics extract useful information from incoming heterogeneous big data to make the system aware of the patient and surrounding environment states, and on the other hand, self-aware approaches enable the system to refine its behaviour with respect to the situation (i.e., patient state and environmental state) and adjust *attention* to critical parameters in the system over time (Preden et al. 2015). As an example, in the context of health monitoring, the system defines several priorities for different medical parameters based on the elderly diseases. The priorities indicate the importance level of the parameters. In other words, they specify the data collecting rates from the sensors, the execution time and the order of the data analysis for each parameter. In this way, for instance, the system is more sensitive to heart-related parameters of the user suffering from cardiovascular diseases compared with other parameters. Such adaptivity can be extended to other services (e.g., safety monitoring, etc.) to mitigate impacts of accidents and in general to implement a robust remote elderly monitoring system.

#### 7 Conclusions

Several approaches have been recently proposed to address the daily life requirements of elderly people. However, there exists a lack of comprehensive user-centered study in the literature. In this paper, we studied

state-of-the-art IoT-based elderly monitoring approaches to investigate their advantages and shortcomings from a different viewpoint by considering the elderly requirements at the center of attention. In addition, we introduced a modernized classification and proposed a hierarchical model for elderly-centered monitoring to investigate the current approaches, objectives and challenges in a top-down fashion. Consequently, our study develops a comprehensive perspective on the area, discusses the existing solutions and presents the main objectives and trends that IoT-based systems can provide for future remote elderly care.

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# Paper II

## The Internet of Things for basic nursing care—A scoping review

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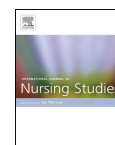




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### Review

## The Internet of Things for basic nursing care—A scoping review



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### ABSTRACT

**Background:** The novel technology of the Internet of Things (IoT) connects objects to the Internet and its most advanced applications refine obtained data for the user. We propose that Internet of Things technology can be used to promote basic nursing care in the hospital environment by improving the quality of care and patient safety.

**Objectives:** To introduce the concept of Internet of Things to nursing audience by exploring the state of the art of Internet of Things based technology for basic nursing care in the hospital environment.

**Data sources and review methods:** Scoping review methodology following Arksey & O'Malley's stages from one to five were used to explore the extent, range, and nature of current literature. We searched eight databases using predefined search terms. A total of 5030 retrievals were found which were screened for duplications and relevancy to the study topic. 265 papers were chosen for closer screening of the abstracts and 93 for full text evaluation. 62 papers were selected for the review. The constructs of the papers, the Internet of Things based innovations and the themes of basic nursing care in hospital environment were identified.

**Results:** Most of the papers included in the review were peer-reviewed proceedings of technological conferences or articles published in technological journals. The Internet of Things based innovations were presented in methodology papers or tested in case studies and usability assessments. Innovations were identified in several topics in four basic nursing care activities: comprehensive assessment, periodical clinical reassessment, activities of daily living and care management.

**Conclusions:** Internet of Things technology is providing innovations for the use of basic nursing care although the innovations are emerging and still in early stages. Internet of things is yet vaguely adopted in nursing. The possibilities of the Internet of Things are not yet exploited as well as they could. Nursing science might benefit from deeper involvement in engineering research in the area of health.

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### What is already known about the topic?

- The Internet of Things has emerged due to the recent technological revolution in developing low-cost, miniaturized, and energy-efficient wireless sensor devices, ubiquitous Internet connectivity and advances in cloud computing.
- Internet of Things is a novel paradigm where objects with unique identities can be integrated into an information network to

provide intelligent services for remote monitoring of health and wellbeing.

- There are several opinion papers that highlight the possibilities of Internet of Things in the field of healthcare. However, the nursing care is rarely mentioned in these writings.

### What this paper adds

- Numerous Internet of Things based solutions are proposed for basic nursing care in hospital environment but the innovations are still only emerging and tested in case studies and usability assessments.

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- The concept of Internet of Things is at present mainly used in technological field and is not yet adopted to nursing research.
- Nursing could benefit from deeper understanding of concepts developed and used by other disciplines.

**1. Introduction**

**1.1. Background**

Modern technology can be exploited to overcome some of the challenges of basic nursing care in hospitals. Basic nursing care is influenced by nursing staff shortness, work environment issues, impractical physical care environments and difficulties in identifying the patients' needs (Jangland et al., 2016; Lasater and Mchugh, 2016; West et al., 2005). On one hand, there is a need to reinforce nursing procedures concerning requirements for basic nursing care, and on the other hand, traditional standalone equipment in hospitals can be upgraded to collect, transfer and process the data efficiently and automatically. As a novel multidisciplinary concept, Internet of Things (IoT) can connect physical and virtual things and provides advanced solutions to combine and use information from heterogeneous sources (Atzori et al., 2010).

The most promising application of advanced technologies in nursing is their ability to support patient safety and quality of care. To ensure quality, safety and value in healthcare, clinical decisions need to be supported by accurate, timely, and up-to-date clinical information (Institute of Medicine, 2011). Nursing informatics, defined as "science and practice (that) integrates nursing, its information and knowledge, with management of information and communication technologies to promote the health of people, families, and communities worldwide." (IMIA Special Interest Group on Nursing Informatics, 2009) incorporates technologies such as tele-healthcare applications, electronic health records, automated data mining and big data technologies.

In addition to the informatics and software applications, sensors and embedded systems development can have a significant role in nursing care. Medical equipment, wearable sensors, and implantable devices are examples which are proposed to assist nursing in hospitals (Cao et al., 2012; Fraile et al., 2010). Proposed software and hardware entities can provide recognizable improvements in basic nursing care although there is a missing part to provide connectivity between different parts and to equip nursing

with a comprehensive intelligent system. Internet of Things is able to fill this gap and have an important role in this domain although it may partially cover and overlap the aforementioned entities (i.e., health informatics and wearable devices).

**1.2. Basic nursing care**

Already the early nursing theorists Virginia Henderson and Florence Nightingale worked to define the role and actions of nurses. The common definition for nursing actions for the best patient outcomes has been a topic of debate. However, it is agreed that basic nursing care, also known as the "fundamentals of care" refers to the essential elements of care that are required by every patient regardless of their clinical condition (Kitson et al., 2010). All basic nursing care actions share three main points: the caring actions are needed by all patients; they are not related to a specific health problem; and they are not directed to a specific health goal (Englebright et al., 2014). In this review, we employ Englebright's et al. (2014) definition for the basic nursing care. The basic caring actions are divided into four activities. The first activity is **comprehensive assessment** including baseline assessment conducted after patient admission to the hospital. **Periodical clinical reassessment** is the second activity that includes regular assessments throughout the hospitalization. The third one as **activities of daily living** consists of personal hygiene, meals and activities. Finally, the last one is **care management** including coordination of care team activities.

**1.3. Internet of Things**

The Internet of things is an advanced network of objects (i.e. things) with unique identities, each of which interconnects or connects to a remote server to provide more efficient services (Atzori et al., 2010). The amalgamation of various fields such as data acquisition, communication and data analysis offers continues connectivity for the objects to collect, exchange and combine data. Consequently, it is possible to achieve inclusive knowledge about the entire system.

According to the specification and functionality of an Internet of Things based system to collect, transmit and process healthcare related data, the architecture of the system can be specified in three layers, the perception layer, the gateway layer and the cloud layer (Al-Fuqaha et al., 2015; Touati and Tabish, 2013). The perception layer (Fig. 1) is defined to capture comprehensive

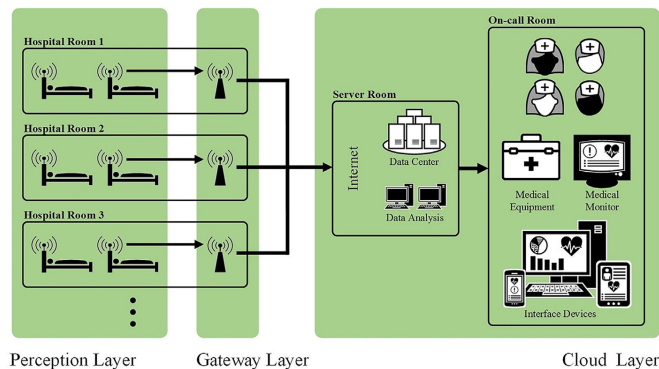


Fig. 1. The architecture of Internet of Things based healthcare systems in a hospital.

health and environmental data using heterogeneous sensors. This layer is the lowest layer and has the most contact with the studied or monitored entities including patients, nurses and objects. Medical devices (e.g. heart rate monitor, pulse oximeter and electrocardiography device), activity and localization devices (e.g. accelerometer and bed presence) and emergency buttons are items that stand in this layer to collect related data.

The gateway layer (Fig. 1) is allocated to connect the sensors to a remote server. The captured data are transmitted via wireless protocols such as Bluetooth and Wi-Fi to a local gateway. The gateway provides continuous connectivity for the sensors or other perception layer inputs and manages interruptions. Then, it transfers the gathered data to a remote or local server called a cloud for further analysis. Recently, the concept of bringing a processing paradigm entitled as fog computing to the vicinity of the sensors was proposed (Bonomi et al., 2014). This smart gateway is defined to improve the functionality of the system (e.g. decreasing latency and increasing consistency in case of the unavailability of an Internet connection) (Rahmani et al., 2015).

The cloud layer (Fig. 1) is the third and most remote section of the Internet of Things system. All the acquired data are transferred to the cloud via the gateway. The cloud can be obtained either via Internet connected remote servers provided by third parties or by local servers connected to local hospital information system (HIS) to provide more protective privacy and security. Using high processing power in the cloud platform, data analytics, data fusion and analysis are used to further process and develop the data (server room in the figure). The results of data processing can then be used in patient care. Real-time/offline data visualization of patients and their surroundings are available via monitors and interface devices (e.g. smartphones and tablets). The system could also enable healthcare personnel for instant responses, feedback and setting adjustments via an administration control panel. Moreover, providing more comprehensive services, such data processing could send feedback to devices used in nursing and patient care to update their configurations automatically.

The cloud layer (Fig. 1) is the third and most remote section of the Internet of Things system. All the acquired data are transferred to the cloud from the gateway. The cloud can be provided in two approaches. The first approach is obtained via Internet connected

remote servers provided by third parties. The second one is achieved by local servers connected to local hospital information system (HIS) to provide more protective privacy and security. Using the high processing power in the cloud platform, data analytics, data fusion and reasoning are implemented to obtain new knowledge and results regarding incoming and stored data (server room in the figure). Afterward, the related obtained results along with collected data are provided for nurses. Real-time/offline data visualization of patients and their surroundings are available via monitors and interface devices (e.g. smartphones and tablets). The system could also enable healthcare personnel for instant responses, feedback and setting adjustments via an administration control panel. Moreover, providing more comprehensive services, it could send feedback to nursing equipment and update their configurations automatically according to the patients' and professionals' requirements.

Consequently, the Internet of Things enabled system is a paradigm that consists of embedded technologies of sensing, connecting and processing to bring advanced applications and services anyplace and anytime for different fields, especially in healthcare and nursing. Therefore, the usage of Internet of Things based systems as the state of the art in health sciences and basic nursing care, can influence improvements in the quality and safety of patient care.

#### 1.4. Study objective

In this scoping review we introduce the concept of Internet of Things to nursing by exploring the current literature to identify the extent, range, and nature of the literature on the Internet of Things in basic nursing care in the hospital environment. In addition, we introduce recent innovations utilizing the Internet of Things concept in basic nursing care in the hospital environment.

## 2. Methods

We used a scoping review methodology, which can be used for mapping the size and scope of research on a topic, synthesizing findings, and identifying gaps in the literature (Grant and Booth, 2009). This is an appropriate approach given that we expect to find papers with diverse methodologies and evidence only emerging in

**Table 1**  
The search terms and databases.

Database	Search terms	Number of papers found	
Pubmed	"Internet of Things" OR "IoT"	429	
	"Nursing informatics"	1096	
Cinalh	"Internet of Things" OR "IoT"	29	
	"Nursing informatics"	965	
Scopus	"Internet of Things" OR "IoT"	251	
	"Nursing informatics"	1148	
Google Scholar	("Internet of Things" OR "IoT") AND ("Nursing" OR "Hospital")	32	
ScienceDirect	("Internet of Things" OR "IoT") AND ("Nursing" OR "Hospital")	15	
SpringerLink	("Internet of Things" OR "IoT") AND ("Nursing" OR "Hospital")	7	
IEEE xplore	("Internet of Things" OR "IoT") AND ("Nursing" OR "Hospital")	77	
	"Hygiene" AND ("Nursing" OR "Hospital")	26	
	"Incontinence" AND ("Nursing" OR "Hospital")	27	
	"Sleep" AND ("Nursing" OR "Hospital")	247	
	"Respiration" AND ("Nursing" OR "Hospital")	194	
	"Fall" AND ("Nursing" OR "Hospital")	437	
	ACM DL	("Internet of Things" OR "IoT") AND ("Nursing" OR "Hospital")	8
		"Hygiene" AND ("Nursing" OR "Hospital")	12
		"Incontinence" AND ("Nursing" OR "Hospital")	1
		"Sleep" AND ("Nursing" OR "Hospital")	6
	"Respiration" AND ("Nursing" OR "Hospital")	0	
	"Fall" AND ("Nursing" OR "Hospital")	23	

**Table 2**  
Summary of the analysis.

Activity	Topics	Articles	IoT Layers		Data Collection			Target Group		Design		Paper Type		Year	Country
			Perception	Gateway	Cloud	Patient	Nurse	Environment	Children	Adults	Elderly	Discussion	Empirical/Methodology		
Periodical clinical reassessment	Vital signs	Hart et al. (2010)	✓	-	-	-	-	-	✓	-	-	-	✓	2010	CAN
		Hu et al. (2010)	✓	✓	-	✓	-	-	✓	✓	-	-	✓	2010	USA
		Andre et al. (2010)	✓	✓	-	✓	-	-	✓	✓	-	-	✓	2010	BEL
		Zito et al. (2011)	✓	✓	-	✓	-	✓	✓	✓	-	-	✓	2011	IRL, ITA
		Donnelly et al. (2012)	✓	-	-	✓	-	-	✓	✓	-	-	✓	2012	GBR
		Fang et al. (2012)	✓	✓	-	✓	-	-	✓	✓	-	-	✓	2012	CHN
		Huang et al. (2013)	✓	✓	-	✓	-	-	✓	✓	-	-	✓	2013	TWN
		Morjan et al. (2014)	✓	✓	✓	✓	-	-	✓	✓	-	-	✓	2014	RIJBAW, IRL
		Liu and Hsu (2013)	✓	-	✓	✓	-	-	✓	✓	-	-	✓	2014	TWN
		Shi-Lin et al. (2015)	-	✓	-	✓	-	-	✓	✓	-	-	✓	2015	CHN
		Liu et al. (2015)	✓	✓	✓	✓	-	-	✓	✓	-	-	✓	2015	TWN
		Gilder et al. (2016)	✓	-	✓	✓	-	-	✓	✓	-	-	✓	2016	USA
		Michard (2016)	✓	✓	✓	✓	-	-	✓	✓	-	-	✓	2016	SUI
		Nachabe et al. (2015)	✓	-	✓	✓	-	-	✓	✓	-	-	✓	2015	FRA
		Huang et al. (2015)	✓	-	-	✓	-	-	✓	✓	-	-	✓	2015	CHN, USA
Martinez-Martinez et al. (2014)	✓	-	✓	✓	-	-	✓	✓	-	-	✓	2014	ESP		
Medication		Jara et al. (2014)	-	✓	✓	✓	-	✓	✓	-	-	✓	2014	ESP	
		Jara et al. (2010a)	✓	-	✓	✓	-	✓	✓	-	-	✓	2010	GBR	
		Jara et al. (2010b)	✓	-	✓	✓	-	-	✓	✓	-	-	✓	2010	ESP
		Larajon et al. (2012)	-	-	✓	✓	-	✓	✓	-	-	-	✓	2012	PRT
		Jara et al. (2014)	✓	✓	✓	✓	-	-	✓	✓	-	-	✓	2014	ESP
		Zhang et al. (2015)	✓	-	✓	✓	-	-	✓	✓	-	-	✓	2015	CHN
		Hua-li et al. (2015)	-	-	✓	✓	-	-	✓	✓	-	-	✓	2015	CHN
		Biswas et al. (2010)	-	-	✓	✓	-	-	✓	✓	-	-	✓	2010	SGP
		Rofouei et al. (2011)	✓	-	✓	✓	-	-	✓	✓	-	-	✓	2011	USA
		Liu and Hsu (2013) <sup>a</sup>	✓	-	✓	✓	-	-	✓	✓	-	-	✓	2013	TWN
Activities of daily living	Sleep detection	Ronaritu et al. (2013)	✓	-	✓	-	-	✓	✓	-	-	✓	2013	USA	
		Zhu et al. (2015)	✓	-	✓	-	-	✓	✓	-	-	✓	2014	JPN	
		Liu et al. (2015) <sup>a</sup>	✓	-	✓	-	-	-	✓	✓	-	-	✓	2015	TWN
		Ang et al. (2008)	-	✓	✓	✓	-	-	✓	✓	-	-	✓	2008	MYS
		Secretion		-	✓	✓	-	-	✓	✓	-	-	✓		

Table 2 (Continued)

Activity	Topics	Articles	IoT Layers		Data Collection			Target Group		Design		Paper Type		Year	Country
			Perception	Gateway	Cloud	Patient	Nurse	Environment	Children	Adults	Elderly	Discussion	Empirical/Methodology		
Fall detection		Wai et al. (2010a)	✓	✓	✓	✓	✓	✓	✓	✓	-	-	✓	2010	SGP, BRN, FRA
		Wai et al. (2010b)	✓	✓	✓	✓	✓	✓	✓	✓	-	-	✓	2010	SGP, BRN, FRA
		Yamada et al. (2010)	✓	-	-	-	-	✓	✓	✓	-	-	✓	2010	JPN
		Wai et al. (2011)	✓	✓	✓	✓	✓	✓	✓	✓	✓	-	✓	2011	SGP, BRN, FRA
		Nilsson et al. (2011)	✓	-	-	-	-	✓	✓	✓	-	-	✓	2011	SWE
		Fuketa et al. (2014)	✓	-	-	-	-	✓	✓	✓	✓	-	✓	2014	JPN
		Huang et al. (2009)	-	✓	-	-	-	-	✓	✓	✓	-	✓	2009	TWN
		Rawashdeh et al. (2012)	-	✓	✓	✓	✓	-	✓	✓	-	-	✓	2012	USA
		Visvanathan et al. (2012)	-	✓	✓	✓	✓	-	✓	✓	-	-	✓	2012	AUS
		Chou et al. (2013)	✓	-	-	-	-	-	✓	✓	-	-	✓	2013	TWN
		Enayati et al. (2014)	-	✓	✓	✓	✓	-	✓	✓	✓	-	✓	2014	USA
		Gatrinucci et al. (2014)	-	✓	✓	✓	✓	-	✓	✓	-	-	✓	2014	ITA
		Schwarzmeier et al. (2014)	✓	-	-	-	-	-	✓	✓	-	-	✓	2014	DEU
		Sriborrinux et al. (2014)	✓	-	-	-	-	-	✓	✓	-	-	✓	2014	THA
	Marmun et al. (2014) <sup>a</sup>	✓	✓	✓	✓	✓	-	✓	✓	-	-	✓	2014	FJI, BGD, IRL	
Activity monitoring		Gatrinucci et al. (2015)	-	✓	✓	✓	✓	-	✓	✓	-	-	✓	2015	ITA
		Hu et al. (2010) <sup>a</sup>	✓	✓	-	-	-	✓	✓	✓	-	-	✓	2010	USA
		Schwarzmeier et al. (2014) <sup>a</sup>	✓	-	-	-	-	-	✓	✓	-	-	✓	2014	DEU
Care management	Decision making support system	Sriborrinux et al. (2014) <sup>a</sup>	✓	-	-	-	-	-	✓	✓	-	-	✓	2014	THA
		Brubala et al. (2014)	-	✓	✓	✓	✓	✓	-	✓	✓	-	✓	2014	ESP
		Manate et al. (2014)	-	✓	✓	✓	✓	-	✓	✓	-	-	✓	2014	ROU, GBR
		Boyi et al. (2014)	-	✓	✓	✓	✓	-	✓	✓	-	-	✓	2014	CHN
		Abinaya and Swathika (2015)	-	✓	✓	✓	✓	-	✓	✓	-	-	✓	2015	IND
		Ashwarya et al. (2015)	-	✓	✓	✓	✓	-	✓	✓	-	-	✓	2015	IND
		Michard (2016) <sup>a</sup>	✓	✓	✓	✓	✓	-	✓	✓	-	-	✓	2016	SUI
		Alharbe et al. (2013)	-	✓	✓	✓	✓	-	✓	✓	-	-	✓	2013	SAL, GBR
		Gatrinucci et al. (2015) <sup>a</sup>	-	✓	✓	✓	✓	-	✓	✓	-	-	✓	2015	ITA





the literature concerning Internet of Things based innovations in basic nursing care settings (Levac et al., 2010). We followed the scoping review guidelines of Arksey and O'Malley (2005) in five stages: 1) identifying the research question 2) identifying relevant studies 3) defining a relevant study selection 4) charting the data and 5) collating, summarizing and reporting the results.

We explored the following questions:

1. How is the Internet of Things used in basic nursing care?
2. What are the benefits of using the Internet of Things in basic nursing care?

### 2.1. Identifying relevant studies

The literature search was conducted in eight databases: Pubmed, Cinahl, Scopus, ScienceDirect, ACM DL (Association for Computing Machinery Digital Library), IEEE Xplore DL (Institute of Electrical and Electronics Engineers Digital Library), Google Scholar and SpringerLink. The databases were selected to cover the fields of the multidisciplinary research topic. The search was conducted in March and April 2016. Moreover, an additional search in the three nursing databases was conducted in September 2016 to include the wide range of nursing informatics literature to the review. At first all the nursing related databases were searched using a Boolean combination of the terms "Internet of Thing" OR "IoT" and the technological databases were searched for "Internet of Things" AND "Nursing" OR "Hospital". The second search was conducted only in technological databases replacing the term Internet of Things with the chosen basic nursing care terms to find detailed information. These terms were chosen to describe the aspects that are objective and detectable. Because of the novelty of the concept of Internet of Things, no time limit was used in first search. However, the search concerning nursing informatics was limited to the years 2006 to 2016. The review was limited to English language publications. The complete search strategy for each electronic database is listed in Table 1.

### 2.2. Study selection

The inclusion criteria were 1) a scientific peer-reviewed publication describing an Internet of Things based solution for basic nursing care 2) the Internet of Things solution is used or proposed for hospital environment 3) the term Internet of Things is used in the paper 4) the paper is a clinical study, a review, a commentary, an editorial or a conference proceeding. The exclusion criteria were 1) the paper describes only a technical design's development 2) the Internet of Things solution is used only for patient monitoring outside the hospital environment 3) the Internet of Things solution is only used for self-monitoring 4) the publication is a book, a book chapter, a magazine or a letter.

### 2.3. Charting the data

Information on authors, their country and publication year were collected. The type of the article and study design were analyzed. The Internet of Things innovations were identified and labelled to describe the basic nursing care topics. The technical development state of the three layers of the Internet of Things based system architecture was identified. Also the main target patient group was specified into children, adults and the elderly, although if no patient group was mentioned in an article, adult patients were chosen. The results of the analysis are collected in Table 2.

## 3. Results

### 3.1. Description of process and findings

Of the 5030 articles originally identified, 149 articles were removed as duplicates. The titles were screened and 4615 papers were excluded as non-relevant to the topic. 265 papers were chosen for closer assessment and identified as potentially relevant. 93 full-text articles were assessed for eligibility, and finally 62 were included in the qualitative synthesis (See Fig. 2 for the flow diagram). Despite the large number of articles of the search for the term "nursing informatics", only one article met the inclusion criteria.

The vast majority of the articles were peer-reviewed proceedings of technological conferences. These included descriptions of Internet of Things based innovation methodology or methodology tested in a case study or usability tests in the hospital environment. Only one article was published in a nursing journal, two in medical journals, and all other articles were published in technological journals. The journal articles did not differ from peer-reviewed proceeding papers in study designs. We found no clinical trials with comparisons or randomized designs. The articles were published between the years 2008–2016 and they were from 30 countries across four continents. Most of the Internet of Things solutions were targeted to adult and elderly patients with chronic diseases. Only a few were designed for a pediatric population. The data used in the Internet of Things solutions were collected in most cases from patients and the environment and more rarely from nurses. Most of the innovations proposed were related to vital signs detection and were set under **periodical clinical reassessment** activities of basic nursing care. The other topics in **periodical clinical reassessment** activities were neonatal monitoring, pain management and medication. **Comprehensive assessment activities** included topics of hygiene and comfort. Physical activity, fall detection, sleep, and secretion monitoring were set under **Activities of daily living**. Finally, **care management** activities included topics of decision making support, tracking personnel, patients and devices, and nurse calling system. Some of the topics could have been set under several activities, but only one was selected. The findings are described in Table 2.

### 3.2. Internet of Things based innovations for basic nursing care in the hospital environment

#### 3.2.1. Periodical clinical reassessment

With Internet of Things-based solutions **vital signs** can be recorded using wireless devices connected to a gateway (Hart et al., 2010; Shi-Lin et al., 2015), body worn wireless sensors (Andre et al., 2010; Donnelly et al., 2012; Huang et al., 2013) or ambient sensors attached on walls or objects (Güder et al., 2016; Mamun et al., 2014; Huang et al., 2015; Zito et al., 2011). Wireless detection systems have the advantage of giving patients real-time dependable and continuous monitoring without causing any inconvenience to patients (Hu et al., 2010). A good example is a cuffless noninvasive measurement of blood pressure using pulse wave transit time as a part of a multifunctional device, containing continuous measurement of seven lead electrocardiography, respiration, temperature, blood pressure, peripheral capillary oxygen saturation, the motion state of a patient in real time (Fang et al., 2012). The heart rate of a patient can also be detected using a wireless ring probe (Huang et al., 2013) or a versatile system which detects electrocardiography, heart rate, respiration waveform and rate, skin temperature and motion with a single wearable sensor (Donnelly et al., 2012). The triggering algorithms are set to alarm for early recognition of patients requiring urgent attention. Some of the innovations have the advantage of detecting both physiological parameters and

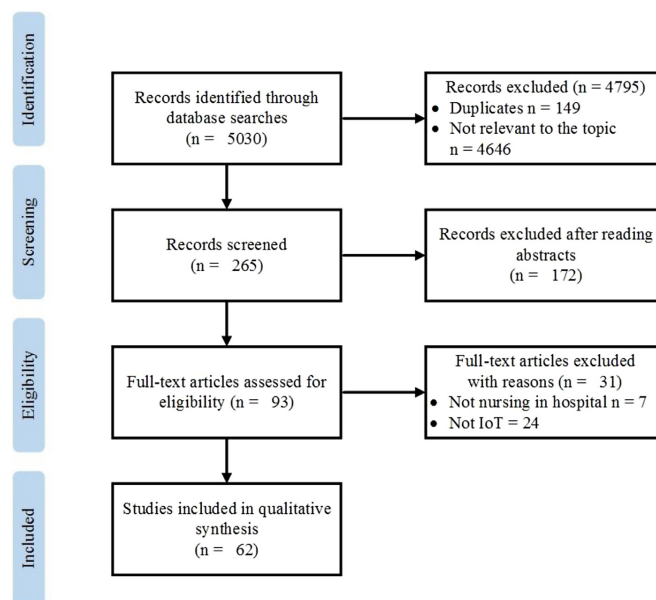


Fig. 2. Flow diagram of literature search modified from PRISMA (Moher et al., 2010).

tracking patients movements using the same hardware (Donnelly et al., 2012; Hu et al., 2010; Mamun et al., 2014).

Several systems for non-invasive and continuous respiration monitoring have been developed both for adults and children. Respiratory rate and pattern can be detected contactless from chest movements, using ultra-wideband technology (Huang et al., 2015; Zito et al., 2011). The sensor can also be connected into a patient's nasal prongs (Andre et al., 2010) or attached into a breathing mask (Güder et al., 2016) to detect respiration through airflow humidity changes. Humidity changes ionic conductivity which can be measured electrically and the data can be further transmitted to a smartphone or tablet computer for post-processing (Güder et al., 2016). An intelligent contact-free sensing pad under the patient on a hospital bed can also measure respiration by recording the changes in the capacitive coupling between the traces of the pad and correlating them to respiration (Hart et al., 2010).

For **neonatal monitoring**, detection of respiration and the possible apnea of an infant can be done by obtaining a breathing signal from an infant's chest vibration. An algorithm is applied to locate the chest of the infant due to possible movement and to set off an alarm in case of apnea (Huang et al., 2015). Also for the use of neonatal intensive care unit nurses, a newborn's physiological parameters, such as heart rate and temperature, and the environmental parameters, such as humidity of the incubator, can be detected via a wireless sensor network (Nachabe et al., 2015). The sensors are connected to a data hub device provided with a software agent for sensed data preprocessing and the server publishes the data into the hospital information system. In addition to physiological parameter detection, Martinez-Balleste et al. (2014) have proposed an automated pain detection system for infants using data acquisition with wearable sensors, video and audio processing. The system automatically analyses the pain or

discomfort level of an infant and raises alarm upon predetermined conditions.

Considering **medication** in hospital surroundings, Jara et al. (2014, 2010a,b) introduce a pharmaceutical intelligent information system for drug delivery to mitigate adverse drug reactions. In the system, tags, e.g., Radio Frequency Identification, are provided for each medicine; then, utilizing tag readers, the medicine is detected, and related data is sent to the cloud layer. The related data and the patient profile are stored and the need to inform the healthcare personnel about possible consequences (e.g., allergies) and further actions is considered. In a similar manner, Laranjo et al. (2012) also offer a solution using Radio Frequency Identification tags for identifying hospital entities to implement medication control from the prescription to pharmaceutical drug control. Other systems including an intelligent medicine box (Zhang et al., 2015) and a pharmaceutical logistics and supply chain management system (Hua-li et al., 2015) are proposed to monitor and control patient medication and to implement tracing and supply chain management of medicines in hospitals from purchase to provision and distribution.

### 3.2.2. Activities of daily living

**Sleep** detection is in most cases based on vital signs monitoring throughout sleep. Rofouei et al. (2011) have proposed a non-invasive wearable neck-cuff sleep detection tool for the early diagnosis of sleep apnea which provides a summary of possible apnea events and a quantification of the severity of sleep apnea. Also a long term detection of patients' skin temperature using a wireless sensor system provides information of the circadian rhythm of patients (Rotariu et al., 2013). For versatile sleep/off sleep monitoring, basic accelerometer sensors and motion-sensing mattresses can be used to collect information about the sleep activity patterns of patients. Biswas et al. (2010) have successfully

done actigraphy based on body-worn accelerometer sensors to remotely monitor and study the sleep-wake cycle of patients at a nursing home. A soft motion sensing mattress or sensors located under a mattress can also collect data about physical activities in a bed (Liu et al., 2015; Zhu et al., 2015; Liu and Hsu, 2013). The corresponding digital signals collected by the mattress sensors are classified into different events such as on/off bed, sleep posture, pressure distribution, movement counts, respiration and heart rate (Liu and Hsu, 2013).

Considering Internet of Things related systems, Ang et al. (2008) have introduced a wireless intelligent incontinence management system to monitor **secretion** and to transmit wetness data to a central system and then further to alert the nurses via SMS. Similarly, Wai et al. (2010a,b) present a system comprising three Internet of Things layers. The first layer is defined to sense diaper wetness. The second layer is specified to provide a wireless connection for the sensors in the hospital. Finally, the third layer handles system operations, provides access to patients' incontinence profiles and sends notifications in case of detecting soiled diapers. To implement the notifications system more efficiently, a smartphone reminder is also integrated into the system (Wai et al., 2011). Various solutions including disposable wet sensors placed inside of diapers are also proposed. They are defined to detect diaper wetness and to transmit the data to the cloud for further actions (Fuketa et al., 2014; Nilsson et al., 2011; Yamada et al., 2010).

A patient alert system and a passive **fall monitoring** system are proposed by Huang et al. (2009) and Schwarzmeier et al. (2014) respectively to provide instant position information and emergency situation detection. A motion monitoring system, including five accelerometer sensors and a 3D avatar (an embodiment of a person) to illustrate the movements, is offered to reduce falls (Rawashdeh et al., 2012). Fall prevention systems are also introduced to notify the nurses about high risk fall activities (Visvanathan et al., 2012) and bed falling (Chou et al., 2013). Context-aware systems are specified to implement fall detection using visual sensors (Bian et al., 2015). In this approach, a camera is installed on a wall or a ceiling in a room instead of attaching devices to patients. The camera outputs are analyzed by online video processing methods instantaneously and related fall information are extracted and transferred to healthcare personnel's computers (Enayati et al., 2014). Also mobile systems can provide fall detection for hospitals such as a robotic system offered by Mamun et al. (2014). Along with patient condition monitoring, the system is enabled by a camera and a 3D laser sensor detects falls and provides emergency notifications. In addition to fall detection and prevention, there are systems to carry out in-general **activity monitoring** considering patient's activities continuously. Real-time monitoring using a necklace tag is proposed to exploit activity data. This data can be information regarding daily activity-level and level of functional ability (Sriborriux et al., 2014). Providing wireless acute care, a non-contact Doppler sensor is also used to fulfill patient monitoring considering patient's vital signs and motions (Hu et al., 2010).

### 3.2.3. Care management

As Michard (2016) proposes, computers will be able to integrate the historical, clinical, physiologic and biological information necessary to predict adverse events, propose the best therapy and ensure the care is delivered properly. While the data gets bigger it becomes vital to find the relevant information quickly and easily for efficient and accurate **decision making**. Ontology based data modelling is used to classify the records stored in one database (Boyi et al., 2014) and the relationships between sensors and devices can be determined (Manate et al., 2014). With the help of algorithms, the systems can detect diseases and suggest treatments based on statistical calculations based on a big amount of

raw data (Aishwarya et al., 2015). This may be particularly useful in emergency care (Abinaya and Swathika, 2015; Boyi et al., 2014).

A smart hospital system proposed by Catarinucci et al. (2015, 2014) offers localization for entities (e.g., patients, personnel and devices) along with emergency situation management; Carvalho et al. (2015) propose a model for individuals in nursing home framework for **tracking** purpose, and Alharbe et al. (2013) asserts a system to detect people and items in hospitals. Providing a connected network using the Internet of Things and intelligent services in the cloud, also the **nursing calling system** is reinforced in hospitals. An Internet of Things based call light system uses icons and phrases to allow patients to specify their needs when making a nurse call request. Thus, the nursing staffs are informed regarding the purpose of their call upon the initiation of the call light request (Galinato et al., 2015). Also the information of patients and nurses positioning can reinforce the nursing calling system and minimize the time between the patient assistance request and nurse arrival (Kanan and Elhassan, 2015; Sharma and Gautam, 2015).

### 3.2.4. Comprehensive assessment

Hand **hygiene** as a significant method to mitigate infection transmission in hospitals and has been reinforced by Internet of Things related systems. Baslyman et al. (2015) present a real-time hand hygiene monitoring to monitor healthcare professionals in hospital rooms and provide a reminder whether hand hygiene is missed. Asai et al. (2013) also offer a system using sensors and interface devices to encourage individuals to practice hand antiseptics. Moreover, different systems are proposed for hand hygiene monitoring using installed sensors in hospital rooms and user-tags for personnel (Misra et al., 2015; Meydanci et al., 2013; Johnson et al., 2012; Herman et al., 2009). Shhedi et al. (Shhedi et al., 2015) also introduce a system to monitor individuals in hospital rooms. Their system recognizes whether a person enters the room, complies with hand hygiene or leaves the room. Using positioning sensors, their system is enabled to monitor hand movements during hand hygiene. Similarly, a system is proposed by Galluzzi et al. (2015) to monitor hand washing duration in hospitals and to classify hand hygiene movements using wrist worn sensors.

Different from the other proposed solutions used mainly for patient detection and management, Vicini et al. (2012) introduces a novel Internet of Things based device for the **comfort** of hospitalized children. The interactive device enables socialization not only with the hospital personnel but with other people regardless of the illness or hospital environment. By playing active learning games the children are given the opportunity of learning and growing during their experience in hospital and gaining a state of wellbeing (Vicini et al., 2012).

The main Internet of Things solutions identified in this review are summarized in Fig. 3.

## 4. Discussion

The fact that most of the included articles were from technology field can be interpreted at least in two ways. Firstly, the topic of Internet of Things in nursing is at infancy as more research and implementation is required. The technological field has a tradition of testing and publishing new methodologies in early stages in case studies and usability tests. Secondly, the articles in nursing field may have insufficient technical description of used devices or use different terminology for similar technology. Because of the terminological issues, an additional literature search was conducted in September 2016 in nursing informatics. However, it was not very relevant to the topic and only one more article met the inclusion criteria and could be included in the review (Galinato et al., 2015). Our study revealed that nursing informatics research

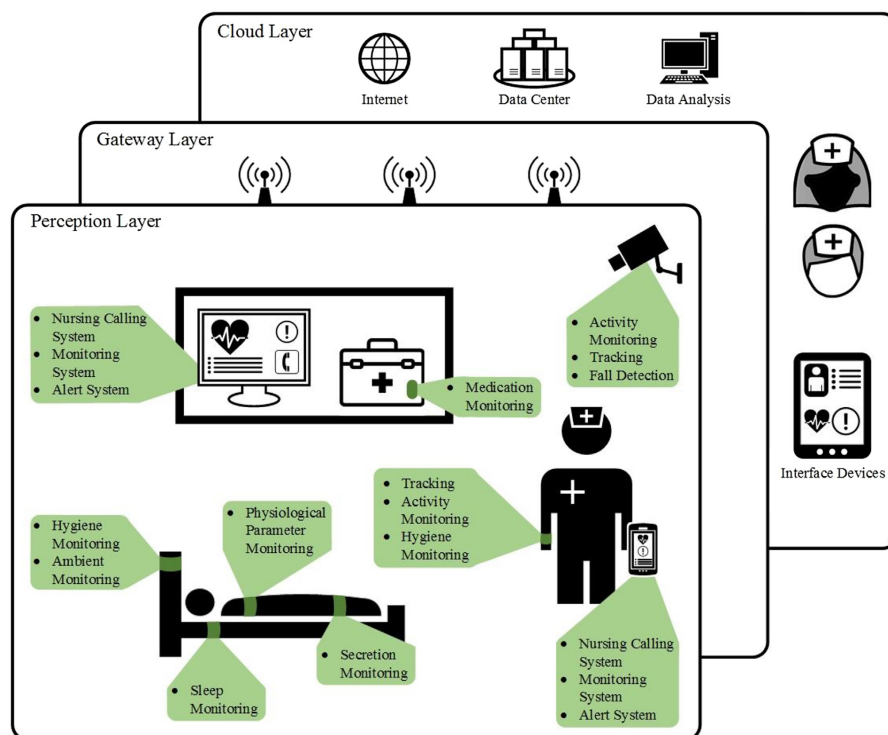


Fig. 3. Internet of Things solutions for nursing in hospital environment.

has not yet focused on Internet of Things and its possibilities in basic nursing care. Nursing informatics mostly concerns integration of the nursing information and knowledge with the information management technologies. However, Internet of Things could offer a new approach to provide real-time wireless health monitoring and cloud computing also in basic nursing care to enable intelligent decision-making support for nurses.

The reviewed papers target at patient centered issues to improve the quality of nursing care with personated health and functioning profiles, and to improve patient safety with automated alert systems and continuous real time monitoring. Innovations in care management provide information about the location and amount of available resources, the means of management and use of big data. Most innovations were based on the monitoring of patients' state giving the nurses vital information and supporting the assessment and decision making processes. While nurses devote a great deal of their time to documentation, medication administration, and care coordination and somewhat less time to actual patient care activities (Hendrich et al., 2008), one of the main advantages of using new Internet of Things solutions in hospitals is the automation of patient data collection and processing utilizing low cost sensors, devices and technologies. Moreover, it enables the hospital system to formalize the incoming raw data into standard electronic health record. This allows nurses to use more time for patient care instead of routine detection of patients' vital signs and transferring patient data to the electronic patient records. Also totally new innovations for problems were

offered; automated tracking of patients and personnel along with fall detection and nurse calling systems give the organization new means of promoting patient safety. The Internet of Things also brings new opportunities to the still unsolved and continuous struggle against the health care associated infections by providing automated hand hygiene detection and reminders.

A valuable property of these innovations is that they are mostly inconspicuous and allow the patient to move more freely which leads to the improvement of the traditionally passivating hospital environment. Wireless solutions promote a feeling comfort for all patients particularly in cases of children and disoriented patients, and also promotes patient safety. Another value is the opportunity to include family in the care by offering real time data remotely, if the family is not able to be present in the hospital (Nachabe et al., 2015; Martinez-Balleste et al., 2014).

Personalized smart services could also be provided for patients in hospitals using Internet of Things based platforms. Acquiring and storing various information (e.g., medical parameters, activities, etc.) from a patient during their hospital stay along with the patient's medical history, provides a comprehensive understanding about the patient's state. Considering this knowledge, it is possible to use data analysis algorithms including machine learning (Murphy, 2012) and pattern recognition (Bishop, 2006) methods to offer personalized services for each patient. For instance, patients would achieve an advantage in diagnosis and treatment procedures by enabling personalized decision making approaches and subsequently minimizing mistakes.

In nursing, the ethical issues related to Internet of Things technologies must be highlighted. In addition to the smart applications that Internet of Things based systems could provide for nursing and hospital environment, the systems should provide security. System security as an important subject in Internet of Things based systems is defined to preserve privacy and improve trust between patients and professionals (Moosavi et al., 2016, 2015; Sicari et al., 2015). It becomes more significant particularly for hospitals in which patients' medical information is available. As discussed in Yang et al. (2012), the potential confidentiality issues can be considered in three parts regarding the three Internet of Things tiers. The perception layer which includes various sensors collecting data from patients and nurses might encounter a data breach. The gateway as an intermediate tier to provide connection between sensors and the cloud might be targeted by many challenges. Finally, the cloud layer containing data centers stores all the patients' and nurses' related information. Addressing security requirements are essentials in Internet of Things based hospital systems and should be satisfied using robust security schemes.

In addition to security and privacy issues, the transparency of the new technology for all stakeholders should be ensured. In health care, informed consent by Internet of Things users or indirect stakeholders can be difficult to obtain if technical knowledge is required (van den Hoven 2013). The nurses need not only the skills to use the new technological solutions, they also need understanding of the wider picture of risks and benefits. These requirements are part of the competence nurses need in technology and informatics in their work in the future (Gassert, 2008).

### 5. Limitations

Since the area of investigation is still in an early stage, the literature is diverse in quality. We included many types of studies to achieve a picture of the field. This has obviously affected the scientific level of the study. However we found it important to include all chosen studies in the analysis to get a good picture of the state of the art. The search terms were not a complete list of all the relevant areas in basic nursing care and this is a limitation. In addition, the concept of the Internet of Things has a broad definition, therefore only papers with sufficient technical description were chosen in the review.

### 6. Conclusions

In conclusion, modern Internet of Things based technology offers various innovations for basic nursing care but most of the innovations are still emerging. Internet of things is yet vaguely adopted in nursing. The possibilities of the Internet of Things are not yet exploited as well as they could. The automation of the patient and hospital environment monitoring and collection and management of data might promote the quality of care and patient safety in basic nursing care but there is still no evidence of effectiveness or efficacy in the literature. In the studied research the proposed technologies are in the testing phase and need to be studied further to ensure their feasibility and security for hospital use. Nursing science might benefit from deeper involvement in engineering research in the area of health and nursing care.

### Authors contributions

Review design: RM, IA, AR, RA, PL, SS; data collection: IA, RM, VT; data analysis: RM, IA; and manuscript preparation: IA, RM, VT, AR, RA, PL, SS.

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# Paper III

## **HiCH: Hierarchical Fog-Assisted Computing Architecture for Healthcare IoT**

**Iman Azimi**, Arman Anzanpour, Amir M. Rahmani, Tapio Pahikkala, Marco Levorato, Pasi Liljeberg, and Nikil Dutt (2017). *ACM Transactions on Embedded Computing Systems*, 16:174:1–174:20



## HiCH: Hierarchical Fog-Assisted Computing Architecture for Healthcare IoT

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The Internet of Things (IoT) paradigm holds significant promises for remote health monitoring systems. Due to their life- or mission-critical nature, these systems need to provide a high level of availability and accuracy. On the one hand, centralized cloud-based IoT systems lack reliability, punctuality and availability (e.g., in case of slow or unreliable Internet connection), and on the other hand, fully outsourcing data analytics to the edge of the network can result in diminished level of accuracy and adaptability due to the limited computational capacity in edge nodes. In this paper, we tackle these issues by proposing a hierarchical computing architecture, HiCH, for IoT-based health monitoring systems. The core components of the proposed system are 1) a novel computing architecture suitable for hierarchical partitioning and execution of machine learning based data analytics, 2) a closed-loop management technique capable of autonomous system adjustments with respect to patient's condition. HiCH benefits from the features offered by both fog and cloud computing and introduces a tailored management methodology for healthcare IoT systems. We demonstrate the efficacy of HiCH via a comprehensive performance assessment and evaluation on a continuous remote health monitoring case study focusing on arrhythmia detection for patients suffering from CardioVascular Diseases (CVDs).

CCS Concepts: • **Human-centered computing** → **Ubiquitous and mobile computing**; • **Computing methodologies** → **Machine learning**; • **Applied computing** → **Life and medical sciences**; • **Computer systems organization** → **Distributed architectures**;

Additional Key Words and Phrases: Internet of Things, Remote Patient Monitoring, Hierarchical Computing, Fog Computing, MAPE-K, Machine Learning

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## 1 INTRODUCTION

There is a growing demand for dependable autonomous health monitoring services for patients suffering from acute diseases [56]. The main function of automated health monitoring systems is to detect medical emergencies and patient health deterioration early enough, as rapid response (i.e., from a few seconds to a few minutes) is instrumental to implement effective countermeasures [45, 53]. Thanks to recent advancements in Internet of Things (IoT) technologies, it is possible to develop remote monitoring services with 24/7 availability for early-detection and preventive purposes.

The IoT paradigm envisions a network scenario where objects (e.g., sensors) are connected and uniquely identified over the global communication infrastructure [9]. Within the healthcare sector, IoT architectures can be decomposed into three main layers [3], as shown in Figure 1. At the first layer, data collection is performed by distributed and mobile sensors. At the second layer, gateways and access points provide continuous connectivity and conventional services such as protocol conversions. These two layers are located at the vicinity of the monitored person. Different communication protocols such as Wi-Fi and Bluetooth LE are often used at this layer to communicate with sensors [54]. In a traditional (i.e., client-server cloud-based) architecture for remote health monitoring, gateways only act as a relay between sensors and remote servers. The third layer consists of cloud resources interconnected to the local edge layers through multi-hop networks. The cloud layer stores and process the sensory data to extract information, and possibly generate notifications as a form of actuation. A broad range of data analytics, machine learning and artificial intelligence algorithms have been implemented at this layer to provide a wide spectrum of services [16]. For instance, the cloud can serve as a pre-processing layer for data whose extracted content is eventually post-processed by experts (e.g., health providers). Alternatively, the extracted information can be stored for later actions (e.g., health coaching) [41, 47].

The cloud-based IoT architecture can provide acceptable performance and reliability to support non-safety and latency critical applications. Examples of such services are several commercial and smart city applications [16]. However, remote patient monitoring systems necessitate a higher degree of dependability, accessibility, and robustness. Therefore, a straightforward extension of the classic client-server model used in the Internet to encompass “things” is not suitable for a large class of IoT applications, among which lies that at the focus of this investigation.

Important issues which interests traditional cloud-based architectures is the occurrence of disconnection from the core network or bandwidth and latency variations. Clearly, these issues can have a severe negative impact on remote health monitoring services, where the end-user is often a patient with critical and time-sensitive needs. For instance, in emergency situations, a delay in establishing a connection may lead to fatal consequences for the patient. In addition, remote monitoring of several patients over time can overload storage and processing capabilities of the cloud, as well as generate an excessive load (i.e., big data) to communication networks, possibly disrupting existing services [13, 37]. Although producing a large volume of data is inevitable in many IoT applications, intelligent pre-processing techniques at the edge can significantly mitigate the volume of the generated data as well as the stress to the network infrastructure.

Alternative approaches propose the use of an intermediate Fog computing layer [15] capable of data processing to enhance reliability and efficiency of the IoT architecture. An intelligent use of such resource can lead to performance sufficient to meet the stringent requirements of healthcare applications. The fog layer is equipped with (limited) computational capacity, which enables the system to locally provide basic, and yet critical, services, and locally controlled distributed systems. Thus, to implement reliable healthcare applications and services, there is the need for effective and application-centric methodologies to map computational and resource management tasks across the layers of the IoT architecture. In our context, an effective model can leverage the available

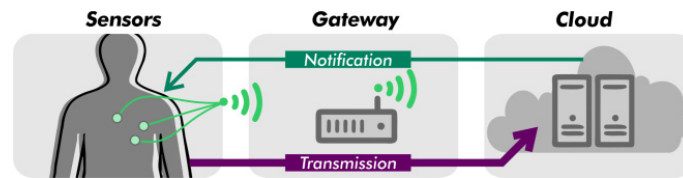


Fig. 1. IoT-based system for remote patient monitoring.

resources and manage flow of data within the system from sensors to computational resources, as well as the reverse flow of control.

In this paper, we present a hierarchical fog-assisted computing architecture, HiCH, for remote IoT-based patient monitoring systems featuring autonomous data management and processing at the edge. We first show that the conventional Observe-Decide-Act (ODA) control strategy [38] is not capable of fully exploiting the features offered by the fog computing paradigm, and then, propose to exploit and customize the concept of MAPE-K autonomic computing – with adaption control loops – introduced by IBM [33] as a more efficient alternative. The main contributions of this paper are as follows:

- We propose a hierarchical computing architecture and a methodology to efficiently partition and accommodate the existing machine learning methods for fog-enabled healthcare IoT systems.
- We customize, enhance, and map IBM’s MAPE-K model for the proposed architecture to better manage system resources.
- We present a closed-loop management technique featuring an adaptive data transmission solution based on patient’s conditions.
- We demonstrate a full system implementation for continuous remote health monitoring case study focusing on arrhythmia detection for patients suffering from CardioVascular Diseases (CVDs).

The rest of the paper is organized as follows. Section 2 outlines background and related work for this research. We detail our proposed approach, HiCH, in Section 3. In Section 4, we demonstrate a full system prototype and evaluate HiCH via a case study. In Section 5, we briefly discuss advantages, limitations and future work of HiCH. Finally, Section 6 concludes the paper.

## 2 BACKGROUND AND RELATED WORK

In this section, we first briefly survey contemporary IoT-based health monitoring systems published in the literature. We then describe the computing models typically deployed in IoT systems.

### 2.1 IoT Architecture and Fog Computing

IoT-enabled systems for health monitoring are typically designed to provide health applications such as early-detection and prediction for users (e.g., patients and health providers) by implementing data collection from patients, data transmission and data analytics. These scheme are broad in scope, ranging from simple to complex monitoring systems. In simple IoT-based monitoring systems, only data collection, transmission and visualization for the users are implemented, and no decision nor analytics concerning patient’s health condition is reported [7]. Hence, these simple IoT-based monitoring systems are insufficient for ubiquitous monitoring that demands the additional capabilities of analytics and decision-making.

Similarly, there are various medical cyber-physical system (MCPS) solutions designed to autonomously actuate tasks w.r.t the sensor data and local decision making. Instances are artificial pancreas for insulin injection regulation [27] and a brain machine interfaces [57]. Such solutions are mostly restricted to typical data processing techniques (e.g., peak detection) using local computational capacity. Therefore, they do not use heavy data analytics such as complex learning algorithms for predictions mainly due their resource constraints.

On the other hand, more complex monitoring systems augment intelligent services using data analytic methods varying from rule-based method to different learning algorithms [32]. Cloud-based services are conventionally responsible for these analytics. In such systems, medical data is collected from the individual via sensors; the data is delivered to cloud servers through a gateway; and extracted information and awareness regarding individual's conditions are shared with users (e.g., health providers). Several IoT-based architectures have been proposed for remote monitoring using this model. Some examples are ECG monitoring systems using wearable devices [10, 41, 52], Early Warning Score (EWS) systems for health deterioration detection [5, 11] and remote physiological parameter monitoring [21, 25, 26, 28, 30]. Unfortunately, these systems critically rely on uninterrupted Internet connections during monitoring; loss of (or degraded access to) Internet connections during monitoring may result in loss of important services such as emergency situation notification and abnormality prediction. Therefore, remote health monitoring with fully cloud-based services run a risk of having flaws in case of patient health deterioration.

In addition to cloud-based IoT systems, there are IoT architectures enabled by fog computing concepts. Fog computing [14, 49] is the concept of extending the cloud computing paradigm to the edge of the network and has been recently proposed to enable new types of services such as local computation, storage, and control for IoT systems. One approach to realize this concept, in particular for the healthcare domain, is by forming an intermediary layer of networked smart gateways between sensors and the cloud [50]. Fog computing offers a variety of advantages to IoT-based applications from both user and system perspectives. Geographic diversity, improved privacy, enhanced reliability and latency reduction are among these benefits [17, 20, 55, 58].

In fog-based architectures, gateway devices perform local data processing along with data transmission to cloud servers. Several research studies have investigated fog computing for health monitoring systems. In these systems, different analytics such as feature extraction [43] and data processing methods [18, 19, 23] are pushed to the fog layer. Moreover, fog computing enables resource management at the local layer, however the management techniques are mostly limited to methods with low computation costs such as rule-based methods [2, 6]. Although these fog-based systems offer notable benefits for remote health monitoring systems, their functionality is bounded due to the limited computational capacity at the edge nodes. Therefore, powerful machine learning algorithms for local decision making cannot be implemented in the fog. Furthermore, the performance, Quality of Service (QoS) and Quality of Experience (QoE) of the system might be degraded since these fog-based algorithms may not as powerful/sophisticated as cloud-based ones.

In sum, ubiquitous health monitoring applications need to provide a high level of quality in attributes such as availability and accuracy, most of which cannot be satisfied by the aforementioned systems. Although both cloud-based and fog-based architectures provide benefits for the monitoring, their applications are insufficient due to their architectural limitations. In this regard, a new architecture is needed to overcome the limitations while leveraging the best features offered by both schemes. This could be achieved by amalgamating both computing paradigms and partitioning the health analytics in a hierarchical behavior. Moreover, a management technique enabled by learning algorithms is required to adjust system behavior with respect to the analytics and based on the context. We overcome these issues in our HiCH approach by presenting an autonomic computing model for the IoT architecture as described next.

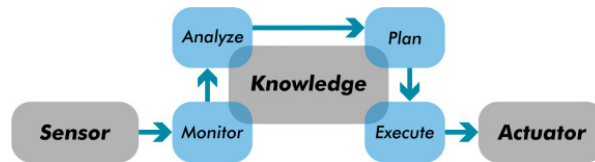


Fig. 2. IBM's MAPE-K model [33].

## 2.2 Computing Models

The computation model plays an important role in IoT systems to efficiently implement various analytics at different architectural layers. Therefore, to enhance different system characteristics, it is crucial to identify, customize, and map a proper computing model to IoT system tiers (i.e., sensor network, gateway, and cloud). Depending on the application, different computing models can be utilized for this purpose.

The conventional Observe-Decide-Act (ODA) management strategy [38] is an existing popular model that is composed of three parts: to manage data collection (Observe), to analyze data and exploit knowledge (Decide) and to implement suitable actions (Act). Due to its centralized nature for analytics and decision making, this model is well-suited for cyber physical systems (CPS) with local computation capacity at the sensor network or centralized cloud-based IoT systems; however it cannot fully exploit available resources in distributed or hierarchical computing systems.

MAPE-K is an alternative computing model introduced by IBM [33]. MAPE-K provides automated management components for computational units and specifies system behaviors. The architecture for MAPE-K model is specified in four different computing components: *Monitor*, *Analyze*, *Plan*, and *Execute* with access to a partially or fully shared knowledge base (see Figure 2).

*Monitor* collects data coming from different resources (i.e., sensors). It is the closest computing component to the sensing fabric. It can also track and determine events that need to be analyzed. *Analyze* provides data analytics to model situations. Data pattern, prediction techniques and meta-data are exploited in this component. *Plan* is in charge of selecting or generating a procedure for the system w.r.t. the inputs received from the *Analyze* component. This procedure can be either a single command or a complicated plan. Finally, *Execute* provides necessary changes in the system, to implement procedures generated in *Plan* component and in general to adjust the behavior of the system.

In this work, we address the reliability, efficiency, and management issues in the existing health monitoring systems by leveraging the concept of MAPE-K and proposing a novel partitioning strategy to hierarchically compute data analytics and manage system resources. Our approach aims at exploiting the best of both worlds, cloud and fog computing.

## 3 HICH: THE PROPOSED SYSTEM

In this section, we present HiCH, a hierarchical computing architecture tailored for fog-enabled IoT systems and designed to leverage the benefits of fog and cloud computing paradigms for remote health monitoring. HiCH offers a new computing and management model with two major contributions:

1. HiCH partitions the health data analytics into two parts: the centralized part located in the cloud, and the distributed part running on fog nodes. In contrast to traditional approaches that use a centralized computing core in the cloud or fog tier, we propose a hierarchical autonomic healthcare system where the computation and knowledge are distributed across different tiers.

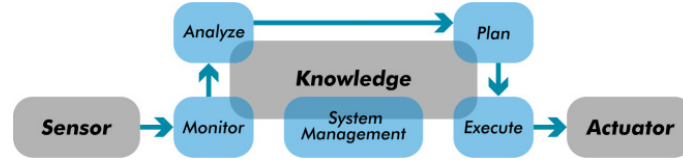


Fig. 3. Enhanced MAPE-K model.

This hierarchical computing scheme enables partitioning of analytics and decision making between the fog and cloud, thereby significantly enhancing the availability, response time and robustness of health monitoring services at the edge. The edge devices (e.g., gateways) are augmented with a high degree of intelligence to provide local monitoring and notification when the cloud connectivity is unavailable or unstable.

2. HiCH deploys a closed-loop system management technique tuned to the patient's conditions (i.e., context). These conditions could be defined according to the patient's medical parameters, activities and surrounding environments. The approach can be used to manage different system resources, although in this paper we only focus on traffic management to control data transmission from the fog to the cloud.

To clarify the functionality and definitions of the architecture, we present and exemplify different components of HiCH via a case study. Below, we first describe our case study of a continuous remote health monitoring system.

### 3.1 Case Study

Our case study focuses on arrhythmia detection in ECG monitoring for patients suffering from CVDs, as an exemplar of a continuous remote health monitoring using HiCH. The deployed system uses a typical single-channel ECG with 250 samples per second, a Microcontroller Unit (MCU), and a wireless transmitter integrated as a sensor node. In the setup, we consider 10-second windows for ECG signals, and the transmission (from fog to cloud) period of 1 minute.

### 3.2 Architecture

The HiCH architecture incorporates the concept of MAPE-K and fog and cloud computing paradigms in remote health monitoring systems, enabling hierarchical partitioning and execution of machine learning algorithms across these computing layers.

As discussed in Section 2.2, MAPE-K model includes 4 computing components, each sharing the system knowledge. To enable hierarchical computing, MAPE-K components need to be properly mapped into the three layers of the IoT system. Furthermore, to fulfill the desired closed-loop behavior for resource management, we propose an enhanced MAPE-K model in which a new component *System Management* is integrated (See Figure 3).

The four MAPE-K components are enabled with feedback in the model. The feedback received from *Execute*, *System Management* is used to periodically tune the computing components with respect to the inputs and the computations in the model.

We distribute and map the 5 components of the enhanced MAPE-K into a 3-tier IoT-based system. Figure 4 illustrates the architecture. The idea is to i) map the heavy training procedures in the cloud while outsourcing the trained hypothesis (e.g., classifier) to the fog nodes to be able to operate in a standalone way, ii) periodically update the hypothesis at the fog, and iii) exploit the knowledge at the edge to enhance resource management via closed-loop control. The blue arrows



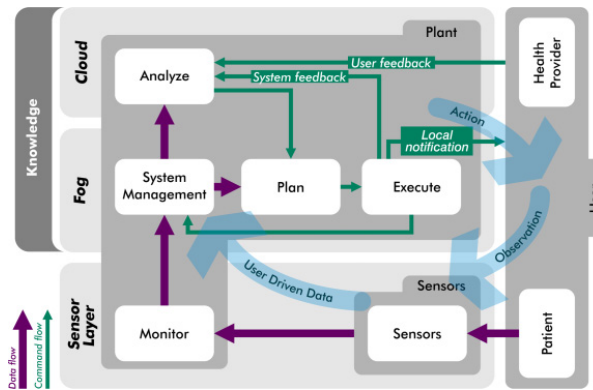


Fig. 4. HiCH: Our proposed IoT-based architecture.

in Figure 4 show the closed-loop behavior: the flow of action to the user and the flow of feedback to the system through the sensors.

*Monitor* is the first computing component in HiCH located in the sensor layer. This component is a bridge between sensors and other units. *Analyze* is the only computing component located in the cloud to process and model complex monitoring conditions. The component receives data from *System Management*. The data contains various information regarding patient health conditions and presumably his surrounding contexts. *Analyze* derives a hypothesis function (i.e., model) from the data and transfers it to *Plan*.

*Plan* is placed in the fog layer to enable local decision making that determines the patient's condition. The decision making is enabled by receiving the hypothesis from *Analyze* and continuous sensory data. The sensor data are received through *System Management*. *Execute* is the second computing component in the fog layer to set system behaviors during monitoring. Finally, *System Management* is the third component in the Fog layer to locally manage the system configurations. It determines the current state of the system considering previous states and the decision received regarding the patient condition. In this architecture, we only allocate data transmission (i.e., bandwidth) management to this component although it can be extended to cover other types of system resources (e.g., energy).

In the following, we present the role of each component in the architecture, and exemplify them via our case study.

**3.2.1 Monitor.** The *Monitor* component is shown in Figure 5(a). It includes an Analog-to-Digital Converter (ADC) to convert sensor analog outputs to digital parameters and signals. Moreover, a Microcontroller Unit (MCU) is integrated to enable data aggregation in a local data storage and data pre-processing such as noise filtering and normalization. Finally, the data are packetized and periodically transmitted to *System Management*. The packet size and the transmission period depend on the data type collected by sensors.

In our case study, a sensor node including a digitized single-channel ECG, a Microcontroller Unit (ATmega328P), and a wireless transmitter (RN42) is used.

**3.2.2 Analyze.** According to the type of sensor data, different machine learning algorithms can be chosen for data analytics in the *Analyze* component (Figure 5(b)). Since the generated hypothesis

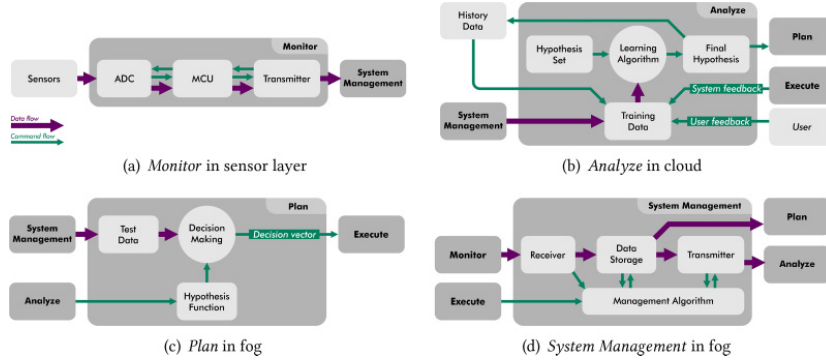


Fig. 5. Major components of HiCH.

function (model) needs to be executed at the edge in the *Plan*, the limited processing power and data storage capacity of the gateways at the edge needs to be considered in the proposed techniques.

To indicate the functionality in HiCH, we assume a simple supervised learning model [1] in *Analyze*. To this end, we define  $h$  as a hypothesis function in a hypothesis set ( $h \in \mathcal{H}$ ) to satisfy:

$$h : \mathcal{X} \rightarrow \mathcal{Y} \quad (1)$$

where  $\mathcal{X} \in \mathbb{R}^d$  represents the input space including  $n$  samples with  $d$  attributes and  $\mathcal{Y}$  is output space that is a vector of patient or context conditions. To simplify the model, we consider an output vector with two possible outcomes, that is, normal and emergency conditions. However, the model can be extended to provide multi-class classifications (more details in [42]).

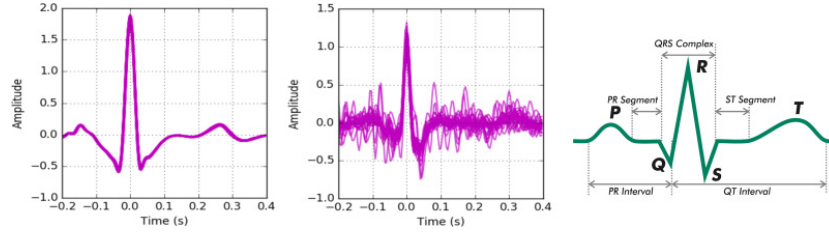
Let us consider a classifier  $h$  inferred by a linear machine learning method (e.g., perceptron or linear support vector machine):

$$h(x) = \text{sgn}(w^T x + b) \quad (2)$$

where  $\text{sgn}(\cdot)$  is a sign function,  $x$  is the input with  $d$  attributes,  $b$  is a bias value and  $w$  is a weight vector inferred by the learning algorithm from the training data. From Equation (2), we observe that the computational complexity of performing a prediction with hypothesis  $h$  is  $O(d)$  in both space and time, since it requires storing the  $d$ -dimensional vectors  $x$  and  $w$  in memory and carrying out an inner product between them.

Nonlinear classifiers may also be fitted to HiCH depending on their time and space complexity. However, some nonlinear classifiers are inappropriate for this architecture. For instance, instance-based learning methods such as K-Nearest Neighbor (KNN) cannot be used in this architecture as the training set would need to be stored in the fog layer, and hence the space complexity would be  $O(dn)$ , where  $n$  denotes the number of training data.

In the *Analyze* component,  $x$  and  $y$  are constructed in *Training Data* (Figure 5(b)). Since sensor data defined in specific time-windows are heterogeneous (e.g., various signals and parameters), we must extract attributes for each time-window.  $x$  is created using the extracted attributes from sensor data and other attribute vectors from *History Data* and *Plan* feedback. In this manner,  $h$  is learned and personalized during the monitoring not only from current sensory data but also from patient history and system feedback (i.e., possible errors). Moreover,  $y$  as the output labels are generated using user feedback (e.g., daily reports in occurred events) and other calibrated devices (e.g., medical and hospital devices).



(a) One minute of normal ECG cycles (60 cycles). (b) One minute of ECG cycles with arrhythmia (67 cycles). (c) An ECG cycle in temporal domain

Fig. 6. (a) and (b) indicates collected ECG cycles. (c) represents a cycle with different temporal features.

$h$  is generated in *Learning Algorithm* using  $x$  and  $y$  from *Training Data* and possible hypotheses from the *Hypothesis Set* (see Figure 5(b)). In this system, the learning is divided into two parts. At the system initialization phase,  $h$  is generated with recorded history data. At runtime,  $h$  is updated during the monitoring with new data.

$h$  is stored in *Final Hypothesis* and subsequently is sent to *Plan* for local decision making. Moreover, values such as the intensity of emergency events are sent to *History Data* for future learning.

In our case study, the *Training Data* unit is responsible for denoising the input signal by using a bandpass filter with the range of 3–45 Hz. Then, ECG cycles are identified by segmenting each window based on RR peaks. To this end, we use the Biosppy toolbox [34] in Python. Figures 6(a) and 6(b) provide examples of normal ECG cycles (60 cycles) and abnormal ECG cycles affected by arrhythmia (67 cycles) referring to a one minute period. To better illustrate the ECG cycle differences, the detected peaks are aligned. As shown in the figures, when abnormality is not present, the signal is almost unchanged across ECG cycles. In contrast, the signals corresponding to arrhythmia present significant variations across ECG cycles.

Moreover, *Training Data* extracts 5 features in the temporal domain [36] for each ECG cycle. The features include QRS complex duration, T wave duration, RR interval, PR interval and ST segment. One ECG cycle in temporal domain is illustrated in Figure 6(c). To extract temporal features, we implement cross-correlation between each cycle and a Triangular signal, defined as:

$$(f * g)(\tau) \stackrel{\text{def}}{=} \int_{-\infty}^{\infty} f^*(t)g(t + \tau)dt \quad (3)$$

where  $f$  is the ECG cycle, and  $g$  is a Triangular signal defined by:

$$x(t) = \begin{cases} 0 & |t| \geq 1 \\ A[1 - \frac{|t|}{T}] & |t| < 1 \end{cases} \quad (4)$$

where  $T$  is the signal length that in our case equals to a QRS complex length, and  $A$  is the amplitude that in our case is a QRS complex amplitude. Using this cross-correlation, we utilize the two signals similarities for detecting peaks in each ECG cycle.

We use linear Support Vector Machine (SVM), a supervised machine learning algorithm, to distinguish between the binary hypothesis (normal vs. arrhythmia). The algorithm is selected because of its low computation cost compared to other alternatives such as neural network backpropagation in which more values (i.e., weights for different layers) should be stored in *Plan*. Moreover, the algorithm represents an acceptable binary classification on the data (see Section 4.3).

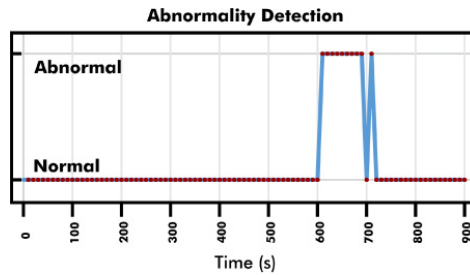


Fig. 7. Abnormality detection implemented in the *Plan*.

The implemented SVM classifier uses the hypothesis function defined by Equation (2) by storing the vector of primal variables  $w$  along with the constant  $b$  and then sending it to *Plan*. Consequently, a single inner product between  $w$  and  $x$  in *Plan* is deployed, instead of expensive computations. For more details see [42]. The classifier is implemented using Scikit-learn [46] in Python.

**3.2.3 Plan.** Similar to the feature extraction approach in *Analyze*, attributes are extracted from the sensor data in *Test Data* unit. Then, *Decision Making* input,  $x' \in \mathbb{R}^d$  including  $d$  attributes, is created (see Figure 5(c)).

The generated hypothesis in *Analyze* is periodically downloaded to *Hypothesis Function* unit. Such feature provides a personalized classifier during the monitoring and subsequently increases the accuracy. The update period (e.g., daily or weekly) is specified with respect to the types of the sensor data.

A decision vector is generated from *Decision Making* unit that indicates the current patient's condition. The vector as the *Plan* output is forwarded to the *Execute* for system actuation.

In our case study, the incoming ECG signals defined in 10 windows is converted to features in *Test Data* unit. Then, the window is classified as normal or abnormal using the current hypothesis function. Finally, the component sends the label assigned to each window to *Execute* component. Figure 7 shows an example where abnormality is detected at the *Plan* component. Decisions are indicated by the red dots, with an abnormal situation detected between the 600 to 720 second interval.

**3.2.4 Execute.** *Execute* fulfills the actuation in the system by forwarding updates to three other parts in the architecture. First, it updates *System Management* to apply changes with respect to the patient condition. Second, it locally notifies patient and health providers about the patient condition; third, it provide a system feedback for *Analyze* by sending the decision to the cloud.

**3.2.5 System Management.** In this architecture, data transmission control is performed by *System Management*. This component includes 4 different units to receive data from the sensor layer, to locally store and organize the data and to transmit it to *Plan* and the remote cloud. Figure 5(d) indicates the units along with data and command flows.

The sensory data are collected via *Receiver* and are stored in *Data Storage*. *Data Storage* is designed to locally store and organize the data (e.g., data structure), to send a complete set of sensory data to *Plan* for local decision making and to implement required data reduction for the transmission to the cloud. *Transmitter* sends the data to the remote servers with a reconfigurable transmission rate with respect to the commands from *Management Algorithm*.

*Management Algorithm* is the processing core of this component that receives updates from *Execute*. It controls data reduction and data transmission rate via communicating with *Data Storage*

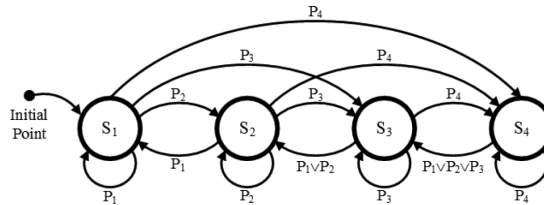


Fig. 8. The state diagram for  $n = 4$  and  $m = 4$ .  $S_{1:n}$  shows system states while  $P_{1:m}$  represents patient's conditions.

and *Transmitter*. We utilize a finite-state machine (FSM) to model *Management Algorithm*. In the model,  $S = [s_1, s_2, \dots, s_n]$  includes  $n$  possible system states where  $s_1$  performs the lowest state (i.e., the most cost-effective setting with the lowest transmission rate from the fog to the cloud) and  $s_n$  represents the highest state (i.e., the most accurate setting with the highest performance). External input of the FSM defines as  $P = [p_1, p_2, \dots, p_m]$  containing patient conditions where  $p_1$  indicates normal condition and  $p_n$  represents high-risk condition.

Regarding the current state and the external input, the next state is determined, and subsequently system configuration is updated. In the state determination, the system instantly jumps from a low state to higher ones to enable rapid response to emergency cases. However, it gradually decreases (one step per iteration) from a high state to lower ones. To indicate the functionality of the proposed FSM, we represent the state diagram of an example in Figure 8.

In our case study, *System Management* is a Python process running on gateways and being responsible for deciding which portion of incoming data should be transferred to the cloud. This is a part of the local processing which dramatically reduces the external bandwidth from the gateway device to the cloud. Given that the decision making is implemented in the fog (i.e. *Plan*), and the data is transmitted to the cloud (i.e., *Analyze*) for updating the model. Therefore, this data reduction does not affect the decision making. In other words, in our case, *System Management* eliminates redundant features in normal conditions although in abnormal cases, it completely transmits the data, from which new information could be obtained for the model.

In *System Management*, data are recorded in two cache storage units defined based on patient's conditions (i.e., normal and abnormal). Figure 9 shows the control flowchart in the *System Management*. We define  $W$  as the number of windows in a transmission period, and  $Q$  as the portion of data that will be transmitted if the patient's condition is normal. In the considered setup, the window length is 10 second, and the transmission period is 1 minute; so  $W$  is 6. The flowchart indicates a loop over each window in the transmission period. In this loop, the cache storage A stores every window of data irrespectively of the conditions, and cache storage B stores only  $Q$  window(s) of data whether patient's condition is normal in the current transmission period. At the end of each iteration, *System Management* sends the data in cache A to the cloud if at least one abnormal window is detected, otherwise it sends the data in cache B.

#### 4 SYSTEM DEMONSTRATION AND EVALUATION

In this section, we present a typical use-case for HiCH where continuous monitoring of ECG signals is used to detect possible arrhythmia. The detection of arrhythmia triggers a notification to the person under monitoring and health providers. In this case study, HiCH is compared with a baseline IoT system introduced in Section 4.1.

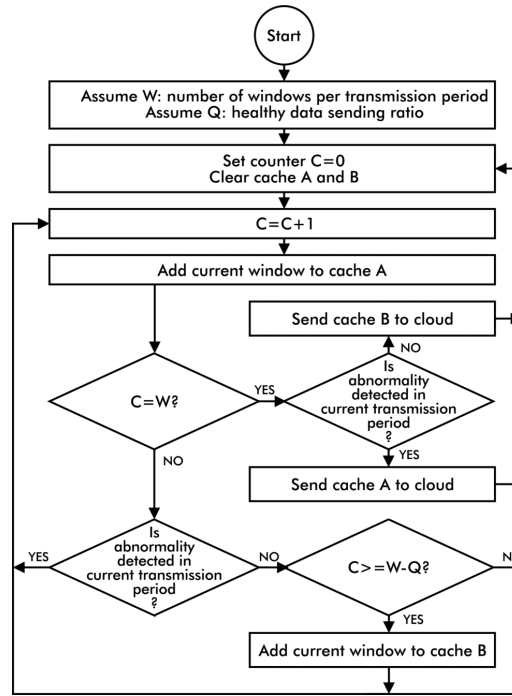


Fig. 9. The flowchart for data transmission from the fog to the cloud.

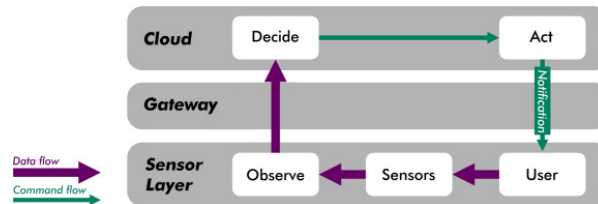


Fig. 10. The IoT-based system modeled by ODA.

#### 4.1 The Baseline IoT System

As discussed in Section 2, there are various IoT-based remote health monitoring systems (e.g., cloud-based and fog-based) that can be selected as a baseline for performance and efficiency comparisons. We consider the conventional and centralized ODA- and cloud-based IoT architecture as the baseline in this study. The baseline IoT system is illustrated in Figure 10.

In this architecture, health data is first collected from the sensor layer. The data is then transmitted to the cloud through an access point, (i.e., gateway device). Afterwards, incoming data is stored

Table 1. The Gateway Devices' Specifications

	Jetson-TK1	HP Compaq 8200 Elite
Processor	Quad-core Cortex A15 + 192 CUDA cores	Quad-core Core i3 2100
Architecture	ARMv7-A	Intel Core
Speed	2.33 GHz	3.10 GHz
RAM	2 GB	16GB
External Storage	16 GB fast eMMC	250GB SATA HDD

and analyzed in the cloud layer to provide actions for the system and notifications for users. In this architecture, no significant computing resources are placed in the gateway and the computing core is centralized in the remote server. The computing core in this architecture can be modeled by ODA control strategy in which *Observe* is placed in the sensor layer and *Decide* and *Act* are placed in the cloud, as shown in Figure 10.

#### 4.2 Setup

For the training and test medical data, we utilize “Long-Term ST Database” available on PhysioBank [29, 35]. Since we use existing data, we emulate the sensing part by transmitting the pre-recorded data from the MicroSD card of the sensor node. We use ATmega328P micro-controller [8] to read the pre-recorded data, which is then sent to an RN-42 Bluetooth module [40] through serial link.

From the available data set, we select a period of 5 hours from a healthy patient along with 5 hours from an individual suffering from a CVD. The samples are used to train a data analysis module in the *Analyze* component. A test data set is also created to assess the performance of the remote classifier whose task is to detect abnormalities. In the test data set, we simulate an emergency scenario by introducing ECG data corresponding to arrhythmia at a random point within a normal ECG signal. To facilitate the analysis, we divide the signal into windows of 10 seconds.

For the fog layer, we use single-board computers. Specifically, Linux-based computing boards are selected to run an Apache server and Python code for the data processing at the fog. In this case study, we used an NVIDIA Jetson-TK1 [44] board and an HP Compaq 8200 Elite Linux machine, each of which presents different characteristics. The HP Compaq 8200 Elite is powered by a Quad-core Core i3 2100 CPU and 16GB RAM, which provides much better performance compared to Jetson-TK1 platform. Table 1 indicates the platforms' specifications.

At the fog layer, a Python service is responsible for receiving data from sensor nodes via a Bluetooth module using the serial communication port. The Python service is also developed to store and process the data. An Apache server is programmed in the gateway for transmitting data to the cloud. The fog device uses TCP protocol to establish a wireless communication link to the cloud server. In order to implement the adaptive behavior which is the core of the proposed architecture, the *System Management* has a set of transmission rates which can be dynamically selected while relaying the data. The rate is controlled concerning normality or abnormality detection in *Plan* component.

In the baseline IoT system, the gateway sends all the data to the cloud using TCP protocol, and waits for the acknowledgment from the cloud server. The cloud server is a Linode VPS (virtual private server) [39] with two 2.50GHz Intel Xeon CPU(E5-2680 v3), 4GB memory and SSD storage drive running Apache web server on Ubuntu Linux.

Table 2. Normalized Confusion Matrix

	Predicted Value	
True Value	TN = 0,97	FP = 0,03
Value	FN = 0,01	TP = 0,99

### 4.3 Accuracy Assessment

We first validate the outcomes of the proposed architecture. To assess the accuracy of detection at the cloud, we use the  $k$ -fold cross-validation technique [1], where we set  $k$  to 10, the defined training set of 10 hours is partitioned into 10 sub-periods where in each experiment, 9 sub-samples are considered as training data and 1 as validation data. The overall accuracy is equal to 0,936 ( $\pm 0,055$ ). Although the portion of ECG signals with arrhythmia might be less than normal ones in practical experiments, we utilized training set with almost equal portions of normal and abnormal ECG data to obtain unbiased results.

In addition to the validation performed using training data set from the same patients, we cross-validate the performance of the system using test data from 4 new patients, whereas the classifier is trained using data from the previous patients. Using the true values and the estimated values, we have the normalized confusion matrix indicated in Table 2, whose  $F_1$  score is also calculated as: 0,98. However, we remark that different implementations of the classifier may produce different results.

In consequence, the algorithm performed an acceptable classification to distinguish between normal and abnormal ECG cycles.

### 4.4 Performance Evaluation

Next, we assess HiCH in comparison with the baseline IoT system from two different perspectives: (i) we consider response time, and (ii) we evaluate data traffic (bandwidth utilization) in both systems.

*4.4.1 Response Time.* We now focus on response latency, a critical metric to measure system response to alert the user in case of emergency. Dividing time latency into data transmission time and computation time, we have:

- a) Data transmission time from the sensor node to the gateway device
- b) Data transmission time from the gateway device to the cloud
- c) Notification transmission time from the cloud to the gateway device
- d) Notification transmission time from the gateway device to the patient (i.e., a node placed in the sensor layer)

and

- $\alpha$ ) Computation time for data analytics in the cloud
- $\beta$ ) Computation time for data analytics in the fog

Therefore, the baseline IoT system's latency is calculated as  $a + b + \alpha + c + d$  while the latency for HiCH is  $a + \beta + d$  (Figure 11).

In our case study, the ECG data sampling rate is 250 samples per second while each sample is 3 bytes. Considering the recording time for a window (10 seconds in our case) and the header, the sensor node should send 8000 bytes (7500 bytes of data + 500 bytes header) per transmission to



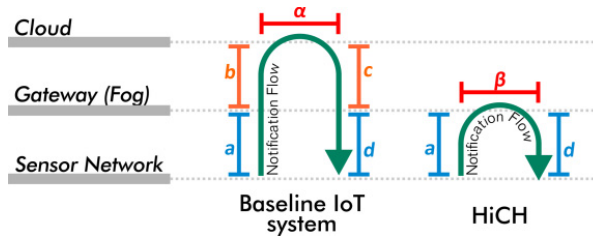


Fig. 11. Response time in the baseline IoT and HiCH.

Table 3. Latency ( $b + c$ ) between the Gateway Devices and Server with Different Connection Networks

	Wi-Fi	4G	3G	GPRS
Spec. (Ping, DL, UL)	2ms 30Mb/s 15Mb/s	20ms 4Mb/s 3Mb/s	100ms 750kb/s 250kb/s	500ms 50kb/s 20kb/s
$b + c$ (ms)	$125 \pm 17$	$147 \pm 16$	$405 \pm 23$	$3686 \pm 4$

the gateway. The transmission module (i.e., RN-42 Bluetooth) in the sensor node takes 651 ms to transmit 8000 bytes using 115200 bit/s baud rate. Therefore,  $a = 651$  ms.

Moreover, sending a 500-bytes notification header using the same module and baud rate takes 43 ms ( $d = 43$  ms). In contrast with  $\{a$  and  $d\}$ ,  $\{b$  and  $c\}$  are not fixed values and depend on the available network specification. Table 3 shows  $\{b + c\}$  values for *Wi-Fi*, *4G*, *3G* and *GPRS* networks, each of which has different latency (i.e., ping time), download and upload speeds. These values were obtained from data transmission for 1 hour monitoring.

The computation time in our case study is measured as follows:  $\alpha$  equals ( $22 \pm 3$ ms), and  $\beta$  (using different boards) equals: ( $27 \pm 2$ ms) using HP and ( $65 \pm 3$ ms) using Jetson-TK1. Given that *Plan* has the most computation burdens compared to the two other components at the edge. The response time for the systems are shown in Figure 12. The response time for the baseline systems (illustrated with violet bars) depends on the network transmission rate while the response time in HiCH system (illustrated with red bars) relies on the computational capacity of the gateway device. Compared to the baseline IoT systems, HiCH reduces the response time when using any of the gateway devices. This improvement is particularly significant when the connection provided by the network is weak or lost. However, we remark that gateway device specification is important in this system. To this end, we also tested HiCH on a less powerful edge device, Raspberry Pi Zero device [51], and obtained the response time of 1414ms.

**4.4.2 Bandwidth Utilization and Storage.** Next we evaluate the bandwidth savings in our system compared to the baseline IoT system, by assessing data transmission from the gateway to the cloud and data storage in the cloud.

We use the cache size to estimate the required bandwidth to transmit the data and the required memory to store the data in the cloud. Table 4 shows the traffic handled by the *System Management* as a function of the parameter  $Q$  (i.e., the portion of data that will be transmitted if the patients condition is normal). The obtained values indicates a significant reduction in the bandwidth utilization over a 1 hour monitoring period if  $Q$  is small. This data traffic reduction is 82% if  $Q$  is 1. Note that if  $Q$  is set to 6, all the data is transmitted to the cloud, so it can be considered the same

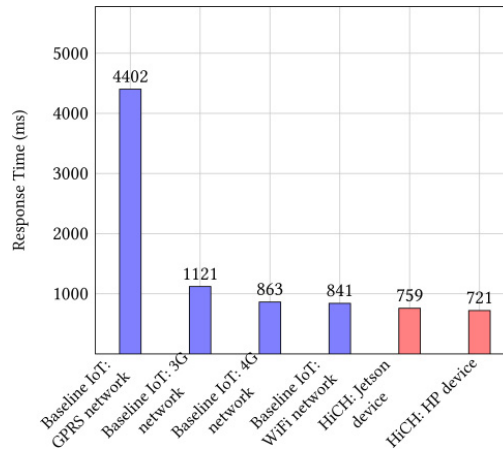


Fig. 12. Response time for different approaches.

Table 4. Data Traffic for 1 Hour Monitoring with Different Q

Q	Data to be transferred to the cloud (KB)	Data description (KB)	TCP overhead (KB)	Total traffic (KB)
1	439	29	13	481
2	879	29	25	933
3	1318	29	37	1384
4	1756	29	49	1836
5	2197	29	61	2287
6	2636	29	73	2738

situation as in the baseline system. This reduction becomes more significant when the number and resolution of monitored vital signs or patient activities is increased.

Similarly, Table 5 indicates the volume of stored data in the cloud for 1 hour monitoring (with 8 minutes abnormality). The volume of data during abnormality detection does not change with varying  $Q$ , due to the maximum transmission rate. However, the stored data in normal condition is remarkably reduced. This reduction of unnecessary data transmission becomes particularly more significant in long-term health monitoring scenarios where large amounts of health data need to be stored in the cloud for every patient.

## 5 DISCUSSION

We now discuss the advantages, limitations and potential of HiCH in remote health monitoring systems from both user and system perspectives.

From the user perspective, enhancing Quality of Service (QoS) and Quality of Experience (QoE) are the main targets in HiCH. Cloud-based systems heavily depend on the connectivity between local devices and the server, and hence, binds the system functionality to the availability of Internet

Table 5. Data Storage for 1 Hour Monitoring with Different Q

Q	Data in normal cond. (KB)	Data in abnormal cond. (KB)	Data stored in the cloud (KB)	Reduction in data size
1	406	355	761	71%
2	787	355	1142	57%
3	1167	355	1522	43%
4	1549	355	1904	29%
5	1929	355	2284	14%
6	2310	355	2665	0%

connection. HiCH, on the other hand, has no constraint on ubiquitous Internet connection due to local decision making and notification.

Security is an essential issue in HiCH as well as in every health IoT application since failures could put lives at risk [50]. We consider our system security as three parts. a) Data transmission security from the sensor network to the fog: Most wireless transmission protocols are recently enabled to encrypt data during the transmission. Using Bluetooth protocol, communication starts with pairing, and subsequently encrypted data is transmitted. In our case study, RN-42 Bluetooth module transfers data using 128-bit AES-CCM encryption [24]. b) Data transmission security from the fog to the cloud: In WiFi and LAN networks, data is encrypted in a higher level using Secure Sockets Layer (SSL) connection as used in our case study. c) Data storage security on the fog and the cloud: An attribute-based encryption (ABE) algorithm provides several data access levels for stored data in fog and the cloud. It has been shown that the ABE algorithm is feasible in IoT applications to hold multi-level data access as well as privacy [4]. Moreover, an end-to-end secure framework for Fog-enabled IoT-systems has been recently introduced to enable efficient authentication and authorization while complex security algorithms perform at the edge [48].

Fully local computing systems are bounded to their processing power and data storage, so sensitivity and specificity of these systems are compromised compared to cloud-based systems. In contrast, HiCH copes with this issue by moving the training phase to the cloud and periodically updating local decision makers. This enables the remote servers to form personalized models and leverage patient medical history in the model building.

Moreover, system response time is reduced in HiCH particularly in case of poor connectivity. This is advantageous to healthcare providers since they can proactively react to possible health deterioration cases. It should be also noted that the processing power and storage capacity of fog devices play an important role in determining the efficiency of the HiCH as shown in our experiment. However, with the current trend of increasing processing power and storage of the edge devices, the significance of this concern is diminishing.

Another possible limitation in HiCH is the choice of the learning algorithm. As we discussed in Section 3, some learning algorithms, such as instance-based learning, might not fit within this system. Hence, in some cases, the accuracy of decisions in HiCH might not be as high as in cloud-based systems. This concern is mostly application-specific, and the range of HiCH-compatible algorithms that are widely used nowadays for machine learning is broad.

Moreover, the closed-loop local control enables a dynamic and personalized resource management in systems where various configurations can be adjusted with respect to patient's conditions. In this paper, we only concentrated on the traffic management between the fog to the cloud,

however HiCH can be enriched to consider more holistic resource management. Our future work in this direction will consider personalized energy management to increase the sensors' battery life.

In addition to the healthcare domain, HiCH can be adapted to other domains, where reliability, punctuality and availability are important, for instance IoT-based home and environmental monitoring applications focusing on early-detection and preventive purposes [9, 31]. Examples are fire early-detection, environmental disaster prevention and home intrusion detection. Moreover, HiCH can be tailored for assistive IoT-based services (e.g., assisted living and assisted driving) targeting people with disability or frailty [12, 22].

## 6 CONCLUSIONS

Considering the life critical nature of remote health monitoring systems, a high level of availability and accuracy is required. IoT-based solutions appear to be a viable scheme to deliver availability and accuracy. However, conventional centralized cloud-based IoT systems need uninterrupted Internet connectivity, which poses challenges in the face of mobility and/or degraded access to the Internet. On the other hand, fully distributed fog-based IoT systems support untethered operation but sacrifice accuracy due to the limited computation capacity at the edge. In this paper, we proposed a novel computing architecture, HiCH, for IoT-based health monitoring systems to leverage the benefits of fog and cloud computing paradigms. The two major contributions of HiCH are: 1) a hierarchical computing architecture for partitioning and execution of machine learning data analytics; 2) a closed-loop management technique enabled by autonomic system adjustment with respect to patient's condition. We evaluated HiCH in comparison with a baseline IoT system and discussed the advantages and limitations of the proposed architecture in remote health monitoring systems. Finally, as a proof of concept, we demonstrated a full system implementation targeting continuous health monitoring for abnormal condition detection using ECG signals.

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# Paper IV

## **Empowering Healthcare IoT Systems with Hierarchical Edge-Based Deep Learning**

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## Empowering Healthcare IoT Systems with Hierarchical Edge-based Deep Learning

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### ABSTRACT

Remote health monitoring is a powerful tool to provide preventive care and early intervention for populations-at-risk. Such monitoring systems are becoming available nowadays due to recent advancements in Internet-of-Things (IoT) paradigms, enabling ubiquitous monitoring. These systems require a high level of quality in attributes such as availability and accuracy due to patients critical conditions in the monitoring. Deep learning methods are very promising in such health applications to obtain a satisfactory performance, where a considerable amount of data is available. These methods are perfectly positioned in the cloud servers in a centralized cloud-based IoT system. However, the response time and availability of these systems highly depend on the quality of Internet connection. On the other hand, smart gateway devices are unable to implement deep learning methods (such as training models) due to their limited computational capacities. In our previous work, we proposed a hierarchical computing architecture (HiCH), where both edge and cloud computing resources were efficiently exploited, allocating heavy tasks of a conventional machine learning method to the cloud servers and outsourcing the hypothesis function to the edge. Due to this local decision making, the availability of the system was highly improved. In this paper, we investigate the feasibility of deploying the Convolutional Neural Network (CNN) based classification model as an example of deep learning methods in this architecture. Therefore, the system benefits from the features of the HiCH and the CNN, ensuring a high-level availability and accuracy. We demonstrate a real-time health monitoring for a case study on ECG classifications and evaluate the performance of the system in terms of response time and accuracy.

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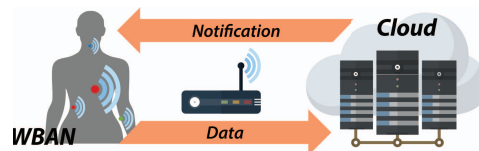


Figure 1: A three-tier IoT-based health monitoring system

### KEYWORDS

Internet of Things, Hierarchical Computing, Health Monitoring, Deep Learning, Convolutional Neural Networks, Electrocardiogram

### 1 INTRODUCTION

Internet of Things (IoT) is increasingly growing in healthcare systems, where patients with acute diseases and at-risk populations such as senior adults and pregnant women can be continuously monitored. Such IoT-based applications are promising alternatives to traditional health services, extending the boundaries of healthcare outside of hospital settings [3, 15]. They mostly target early-detection and prevention of patients' health deterioration as well as allowing independent living of the patients [5].

These systems can be conventionally partitioned into three main tiers in the context of IoT to deliver health monitoring applications [2]. The three tiers are illustrated in Figure 1. First, a wireless body area network (WBAN) including wearable bio-sensors acquires health data. In real-world applications, such data acquisition is mostly performed 24/7 via heterogeneous sensors by which a massive volume of data (i.e., big data) [6, 21] is generated over time. Second, continuous connectivity is enabled via a gateway device located in the vicinity of the WBAN (i.e., edge). The gateway device traditionally operates as a relay between the WBAN and servers although supplementary services can be allocated to the edge. Third, a cloud server is responsible for continuous data analysis methods, enabling real-time decision making.

A wide range of machine learning algorithms is utilized for decision makings in healthcare applications [1, 25]. However, most

of the conventional methods such as traditional neural networks and k-nearest neighbors are inapplicable when the scale of data increases over time, and large amounts of data as big data are generated [32]. In contrast, deep learning methods are promising alternatives in this regard, using strategies in deep architectures to learn hierarchical representations [27, 33]. Such methods can manage large amounts of data while the accuracy improves with the increase of training datasets. Convolutional neural networks (CNN) is one example of the deep learning methods, considered in this work for the IoT-based health monitoring.

In a cloud-based IoT architecture (Figure 1) [11, 12, 23], deep learning methods are perfectly positioned in the cloud servers to take advantages of high-end machines. These machines provide a satisfactory performance with considerably low execution time. However, the response time of the system heavily depends on the availability and quality of Internet connection. Obviously, these systems are unable to satisfy latency-critical applications (e.g. health monitoring), as they have serious consequences for the patients in emergency situations, to the detriment of a delay in establishing a connection.

Moreover, exploiting smart gateway devices at the edge is recently proposed for health monitoring [7, 28, 29]. In this regard, the roles of the gateway devices are extended to implement data processing, through which the collected data is analyzed locally [8]. The gateway devices are equipped with limited computational resources, so a smart task allocation is required to fulfill health monitoring requirements. However, deep learning methods cannot be fully performed on the edge devices, as they are highly expensive in terms of computation time.

Another alternative is a hierarchical computing architecture, in which both local and remote computing resources of the IoT-based system are efficiently exploited. In our previous work [4], we proposed such a hierarchical architecture for a health monitoring system named as HiCH, partitioning a linear machine learning method (i.e., support vector machine with a linear kernel) into different computing components distributed in the three-layers IoT system. The HiCH architecture could utilize the benefits of both edge and cloud computing, where a high level of availability was obtained due to local decision making as well as preserving the performance of the learning algorithm.

In this paper, which is an extension of our previous work presented in [4], we investigate the feasibility of deploying deep learning as a nonlinear machine learning algorithm in the HiCH architecture. The successful integration of deep learning in the HiCH architecture enables health monitoring systems to offer a high level of availability and accuracy. In summary, our main contributions in this work are as follow.

- We present that HiCH is capable of fully employing the Convolutional Neural Networks (CNN)-based machine learning model [31] to perform a real-time heart-related disease detection.
- We demonstrate a real-time health monitoring system implementation for a case study and evaluate the response time of the system.

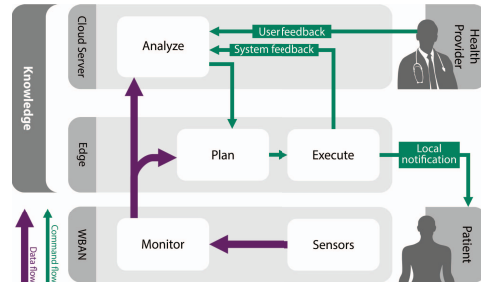


Figure 2: The hierarchical IoT-based architecture

- We evaluate the accuracy of the classification and indicate how the collected data throughout the monitoring can influence the accuracy.

The rest of the paper is organized as follow. In Section 2, we outline a short background of deep learning. Section 3 presents the hierarchical architecture. The demonstration and performance of the proposed system are indicated in Section 4. Finally, Section 5 concludes the paper.

## 2 DEEP LEARNING

Deep learning is one subset of machine learning algorithms that are being used recently in various fields. It has been demonstrated to outperform traditional methods in speech recognition, visual object recognition, and object detection. Deep learning models consist of multiple processing layers that are capable of learning meaningful features of the raw data without domain-level expertise. On the contrary, conventional machine learning methods typically require a considerable amount of domain-level expertise to first extract features and then perform the classification [22].

Convolutional neural networks (CNN) are a class of deep neural networks which are often used with two-dimensional signals such as videos and images. They can learn thousands of objects using millions of images as input datasets. Learning capacity of the CNN can be controlled by varying the depth and breadth of the model [20]. In addition to the two-dimensional signals, CNNs can be exploited with one-dimensional signals such as electrocardiography (ECG) or audio signals.

A typical architecture of CNN for image recognition is formed by stacking multiple layers of computing units with different roles [30]. The main unit in CNN architecture is the convolutional layer that contains learnable filter banks activating when specific features are detected. Max pooling layers leverage CNN architecture to reduce the amount of parameters and enable over-fitting. Fully connected layers typically follow the series of convolutional and max-pooling layers. Role of these layers acts as a classifier for the learned features.

### 3 HIERARCHICAL COMPUTING ARCHITECTURE

In this section, we outline the HiCH as a hierarchical computing architecture enabled by the Convolutional Neural Networks (CNN) to perform real-time heart-related diseases detection using ECG signals. The HiCH exploits the capabilities of edge and cloud computing paradigms, allocating heavy computation tasks of the classification algorithm to the cloud and outsourcing the decision making task (i.e., classifier) to the edge. Therefore, the availability of the IoT-based application is significantly improved, due to local decision making in the case of degraded Internet access or connection loss. Moreover, the performance (e.g., accuracy) of the learning algorithm is preserved in this hierarchical architecture as well as its performance in a fully-centralized computing core in the cloud.

The HiCH architecture employs an enhanced version of the MAPE-K model introduced by IBM [17], distributing the computations in the three-layers IoT system. The model includes 5 different computing components named as *Monitor*, *Analyze*, *Plan*, *Execute* and *System Management*. In this following, we only exploit the first 4 components of this model, as the *System Management* is responsible for managing the system configurations and is out of the scope of this paper. For more details see [4]. Figure 2 illustrates the proposed architecture enabled by the computing components, each of which shares the system knowledge.

#### 3.1 Monitor

The *monitor* is a bridge between the sensors and other computing components, located in the WBAN. It includes a local processing unit for analog to digital conversion, pre-processing methods (e.g., data filtering and compression) and data aggregation in a local data storage. The stored data are periodically transmitted to the edge. The transmission time is determined according to the data and application, which is 10 seconds of the ECG signal in our case study.

#### 3.2 Analyze

Heavy computation tasks including training the hypothesis function (i.e., classifier) are allocated to the *Analyze* that are fully positioned in the cloud machines. As indicated in Figure 3, the hypothesis function is generated using collected data and feedback. The *Training Data* performs required data processing methods before feeding the data to the *Classification Algorithm*.

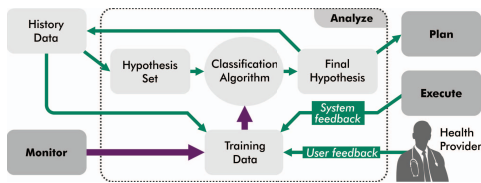


Figure 3: The *Analyze* component in the cloud

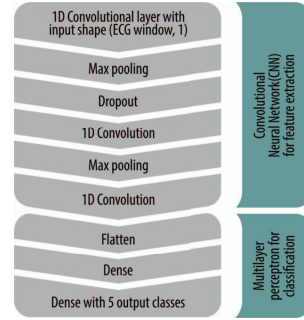


Figure 4: Overall structure of CNN and MLP

In our case study, the *Training Data* is responsible for ECG cycles (i.e., heartbeats) extraction from the incoming ECG signals. Moreover, a fully automatic deep neural network based classifier [31] is employed as the *Classification Algorithm* to detect and classify different abnormalities in ECG signals. In addition, a pre-trained model (i.e., *Hypothesis Set* in the Figure 3) is exploited from ECG datasets. At the beginning of the monitoring, this model acts as a baseline in clinical trials although it is periodically updated over time when new data and feedback are collected.

In the *Classification Algorithm*, first, the meaningful features are automatically determined by leveraging a three-layers CNN. In this method, 16, 32 and 64 neurons are selected as the first, second and third CNN layers, respectively. Moreover, pool size of max pooling is set as 4, and 20% dropout rate is determined to prevent overfitting. The rectified linear unit (ReLU) is used as an activation function [16] in convolutional layers.

Second, the Multilayer Perceptron (MLP) is utilized to implement the classification, using the extracted features from the CNN layers. In this method, one hidden layer with 128 neurons is selected with a learning rate equals to 0.001. Moreover, Tanh and Adam [19] functions are utilized as the activation function and optimization algorithm, respectively. A High-level structure of the classification algorithm including CNN and MLP is shown in Figure 4.

#### 3.3 Plan

The classifier is periodically sent to the *Plan* located at the edge, providing local decision making. Such periodical updates of the classifier enable personalization in the decision making, considering

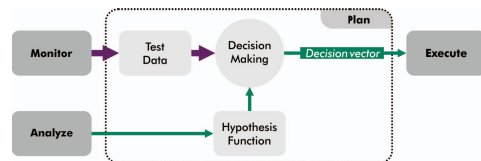


Figure 5: The *Plan* component at the edge

incoming data in re-training of the classifier (at the *Analyze* component) throughout the monitoring. As illustrated in Figure 5, the streaming data received from the *Monitor* component are classified, and a decision vector is generated. Note that similar to the *Analyze* component, required data processing methods (e.g., heartbeat extraction from ECG signals, filtering, and normalization) are fulfilled in the *Test Data*. The decision vector as the output contains the decision class (e.g., patient's health status). It is sent to the *Execute* component for further actuation.

### 3.4 Execute

*Execute* is the second computing component at the edge, implementing the actuation of the system. It sends notifications to the users when an abnormality is detected in the *Plan*. Moreover, it forwards system feedback to the *Analyze*, improving the classifier in terms of accuracy. For example, the model is improved over time by sending the estimated decision class and the true label of data reported by the patient and health provider.

## 4 IMPLEMENTATION AND EVALUATION

We demonstrate the proposed architecture empowered by the CNN via a health case study on ECG classification. In this regard, the decision making is implemented at the edge, sending notifications to the user in case of disease detection. We, first, evaluate response time and availability of the HiCH in comparison with a conventional IoT-based system where the computations are fully performed in the cloud server. Then, we assess the accuracy of the HiCH, indicating the accuracy of decision making at the beginning of the monitoring and its improvement throughout the monitoring.

### 4.1 Setup

We emulate a sensor node and use the MIT arrhythmia database available at [14, 24, 26] to train and test the classification algorithm. The sensor node emulator is an ESP8266-12E WiFi module which contains an 80MHz 32-Bits RISC microprocessor with 96KB RAM and 4MB QSPI flash memory. The Wifi module connects to a local WiFi network and the microprocessor is able to read a Micro SD card via SPI communication. The ECG data is stored on the Micro SD card. We program the sensor node to read 3600 ECG samples from a file on Micro SD card during a 10-second period and send them via an *upload POST* request to the edge device.

The MIT Arrhythmia database includes totally 48 separate ECG recordings, and the length of each recording is 30 minutes. ECG in this database is stored using a two-lead configuration using 360 Hz sampling rate and digitized with 11-bit resolution. Originally, heartbeats in the database are labeled by two cardiologists. 19 different labels have been used in classifying arrhythmias. However, AAMI [13] recommends that these classes can be divided into five super-classes, namely normal (N), supraventricular ectopic beat (SVEB), ventricular ectopic beat (VEB), fusion beat (F) and unknown beat (Q). These types of arrhythmias are not immediately life-threatening, but still may demand further investigation. Arrhythmias that belongs to this category can be detected from a single heartbeat, which means that shape and other morphological features define the type of the arrhythmia [18].

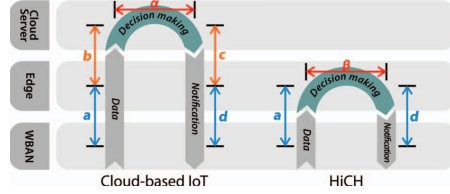


Figure 6: Response time in the conventional IoT-based system and the HiCH

The edge device is an Ubuntu Linux machine running Apache web server, PHP, and Python interpreter services. A PHP script receives the samples file from the sensor node and calls the Python codes for signal processing and decision making. The reply to the sensor node *upload POST* request contains the result of decision making.

To perform the comparison between the HiCH and the conventional IoT-based system, we implement a similar procedure on the cloud machine which is a virtual private server (VPS) with the same OS and services. The VPS runs on two E5-2680 v3 Intel Xeon CPUs at 2.50GHz with 4GB RAM and 40Gbps network.

### 4.2 Response Time

In this section, we assess the performance of the HiCH focusing on the system's response time which is the time period between recording data and notifying the patient in case of emergency. The response time can be divided into different intervals as:

- $a$  = Data transmission time, WBAN to edge
- $b$  = Data transmission time, edge to cloud
- $c$  = Notification transmission time, cloud to edge
- $d$  = Notification transmission time, edge to WBAN (patient)
- $\alpha$  = Execution time, in the cloud
- $\beta$  = Execution time, at the edge

Table 1: Data transmission time using HiCH and the cloud-based IoT with different networks

		Data trans. rate (Kbps)	Trans. time between WBAN and edge (a+d) (ms)	Trans. time between edge and cloud (b+c) (ms)
HiCH	Local Network	30000	10	-
Cloud-based IoT	4G	4000	10	41
	Fast 3G	1500	10	151
	3G	750	10	450
	Fast 2G	450	10	753
	2G	250	10	1490
	GPRS	50	10	5803

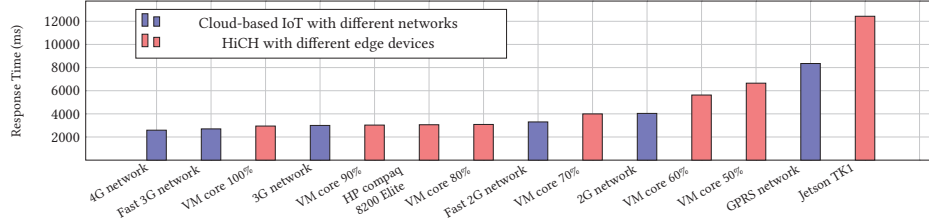


Figure 7: Response time for different approaches using the Cloud-based IoT and HiCH architectures

As indicated in Figure 6, the HiCH response time includes  $a + \beta + d$  while the response time of the cloud-based IoT system is  $a + b + \alpha + c + d$ .

To validate the experiments, we measure the intervals for the two systems using different setups. In this regard, the transmission time is measured via 4G, Fast 3G, 3G, Fast 2G, 2G and GPRS networks. The average transmission time for the two system is represented in Table 1.  $a + d$  as the local transmission equals to  $10ms$  although  $b + c$  varies from  $41ms$  to  $5803ms$  depending on the Internet network.

We measure the execution time of the decision-making process (i.e.,  $\alpha$  and  $\beta$ ) using different edge devices with different CPU performance. In this regard, we utilize an HP Compaq 8200 Elite Linux machine with a quad-core Intel Core i3 CPU at 3.10 GHz and an NVIDIA Jetson-TK1 with a quad-core ARM Cortex A15 CPU at 2.33 GHz. Moreover, we use an Oracle Virtual Machine with a single-core Intel Core i7 CPU at 3.4 GHz and allocate 100%, 90%, 80%, 70%, 60%, 50% of its execution capacity to the computation in each experiment. As the decision-making algorithm in this research is in Python, we measure the CPU performance by counting the number of floating point operations performed per second by Python interpreter (FLOPS). Table 2 indicates the Python FLOPS and the average execution time for the two systems.

In conclusion, the response time of the two systems with different setups is illustrated in Figure 7. The response time of the cloud-based IoT system highly depends on the Internet network.

Table 2: Execution time of the decision making process using HiCH and the cloud-based IoT with different devices

		Execution time (ms)	Python FLOPS
HiCH	VM* Core, 100% Exe. Capacity	2936	17.5
	VM Core, 90% Exe. Capacity	3020	13.8
	HP Compaq 8200 Elite	3049	13.4
	VM Core, 80% Exe. Capacity	3074	13.1
	VM Core, 70% Exe. Capacity	3985	11.1
	VM Core, 60% Exe. Capacity	5617	7.9
	VM Core, 50% Exe. Capacity	6643	7
	Jetson TK1	12425	4.3
	Cloud-based IoT	Cloud Server	2539

\*Virtual Machine

As indicated, the response time of this system with the 4G network is the lowest although it increases when the Internet connection is poor. On the other hand, the response time of the HiCH is determined by the processing power of the edge device. Therefore, by selecting an appropriate edge device, HiCH ensures an acceptable response time.

### 4.3 Accuracy Assessment

We evaluate the accuracy of the ECG arrhythmia classification using the MIT Arrhythmia dataset. In this regard, we divide the dataset into two different datasets (DS1 and DS2) using the division method presented in [9]. Dataset division, where training and testing dataset are generated from separate patients, is called inter-patient paradigm. On the contrary, dataset division where testing and training phase data contains heartbeats from the same patients is called intra-patient paradigm. We ensure unbiased classification accuracy by the inter-patient paradigm, considering patient-specific variances in the data.

In the first step, the ECG classifier is trained by the DS1 dataset, which contains 51020 ECG samples from different patients (i.e., inter-patient). We validate the performance of the classifier using the DS2 dataset. The confusion matrix is specified as Table 3, using the estimated decision for ECG samples and the true labels.

The correct estimates, highlighted in the confusion matrix, are notably high in this initial phase. However, the accuracy might be insufficient particularly for clinical applications as the classifier is trained via general data and inter-patient variation of ECG morphologies is considerably large [10]. Therefore, the model is not specifically trained for the monitored patient.

To address this issue, the accuracy of the classifier is improved over time in our proposed architecture by re-training the classifier via incoming ECG samples from the patient along with labels from

Table 3: Confusion matrix of the classification algorithm

		Estimated Decision				
		Normal	SVEB	VEB	F	Q
True Decision	Normal	<b>40671</b>	905	2615	68	0
	SVEB	642	<b>1148</b>	47	0	0
	VEB	339	2	<b>2874</b>	6	0
	F	275	0	111	<b>2</b>	0
	Q	2	0	5	0	<b>0</b>



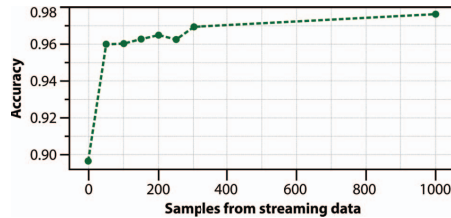


Figure 8: Accuracy improvement by retraining the model with new samples

the health provider (i.e., patient-specific information from ECG morphology). We test the performance of the classifier by randomly selecting 50, 100, 150, 200, 250, 300 and 1000 samples from the DS2 dataset and re-training the initial classification model.

Figure 8 illustrates how the accuracy of the model improves when the model is re-trained. The starting point represents the initial pre-trained model with no knowledge about patient-specific data. As indicated, the accuracy of the classifier at the starting point is less than 0.9. In contrast, the accuracy significantly increases to over 0.96 even if the classifier is re-trained with a small portion (e.g., 50 samples) of the patient data (i.e., intra-patient) throughout the monitoring.

## 5 CONCLUSION

IoT-based health monitoring systems enable at-risk patients to be monitored outside of conventional clinical settings. Such systems are demanded to deliver a high quality of experience as a defect in the service may lead to fatal consequences for the patients. In terms of decision making, deep learning can provide a satisfactory performance as a massive amount of data can be fed to the classification algorithm. In the conventional cloud-based IoT systems, these methods can be fully implemented in the cloud machines. However, these systems are insufficient for a time-sensitive health application due to the dependency of the service to the quality of the Internet connection. Fully distributed edge-based systems are other alternatives although they are incapable of implementing deep learning methods due to the restricted processing power. Another alternative, proposed in our previous work, is the hierarchical computing architecture to partition the learning method in the cloud and edge. In this paper, we investigated the feasibility of empowering the HiCH architecture with the CNN algorithm. We compared the response time of the HiCH with a conventional cloud-based IoT system and indicated that HiCH could ensure an acceptable response time and improve the availability particularly when the connection is poor. In addition, we assessed the accuracy of the system and showed that the accuracy was improved throughout the monitoring, feeding the streaming data to the classification algorithm.

## ACKNOWLEDGMENT

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# Paper V

**Missing data resilient decision-making for health-care IoT through personalization: A case study on maternal health**

**Iman Azimi**, Tapio Pahikkala, Amir M. Rahmani, Hannakaisa Niela-Vilén, Anna Axelin, and Pasi Liljeberg (2019). *Future Generation Computing Systems*, 96:297–308







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## Missing data resilient decision-making for healthcare IoT through personalization: A case study on maternal health



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### HIGHLIGHTS

- A personalized missing data resilient decision-making approach is proposed.
- The approach is presented for a real human subject trial on maternal health.
- Personalized models are defined, exploiting medical and context data.
- A personalized pooling method is introduced to deliver health decisions.
- The proposed approach is evaluated in terms of accuracy of the health decisions.

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### ABSTRACT

Remote health monitoring is an effective method to enable tracking of at-risk patients outside of conventional clinical settings, providing early-detection of diseases and preventive care as well as diminishing healthcare costs. Internet-of-Things (IoT) technology facilitates developments of such monitoring systems although significant challenges need to be addressed in the real-world trials. Missing data is a prevalent issue in these systems, as data acquisition may be interrupted from time to time in long-term monitoring scenarios. This issue causes inconsistent and incomplete data and subsequently could lead to failure in decision making. Analysis of missing data has been tackled in several studies. However, these techniques are inadequate for real-time health monitoring as they neglect the variability of the missing data. This issue is significant when the vital signs are being missed since they depend on different factors such as physical activities and surrounding environment. Therefore, a holistic approach to customize missing data in real-time health monitoring systems is required, considering a wide range of parameters while minimizing the bias of estimates. In this paper, we propose a personalized missing data resilient decision-making approach to deliver health decisions 24/7 despite missing values. The approach leverages various data resources in IoT-based systems to impute missing values and provide an acceptable result. We validate our approach via a real human subject trial on maternity health, in which 20 pregnant women were remotely monitored for 7 months. In this setup, a real-time health application is considered, where maternal health status is estimated utilizing maternal heart rate. The accuracy of the proposed approach is evaluated, in comparison to existing methods. The proposed approach results in more accurate estimates especially when the missing window is large.

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### 1. Introduction

Remote health monitoring systems broadly extend the boundaries of everyday healthcare access particularly for at-risk population groups including pregnant women [1] and senior adults [2]

who may require additional observation. These systems are very promising in the healthcare domain as the individuals can be continuously monitored for early detection, preventive care, and early intervention. The key function of such healthcare systems is to ubiquitously observe and analyze users' health conditions, and subsequently deliver medical early-warning as well as health and wellness coaching.

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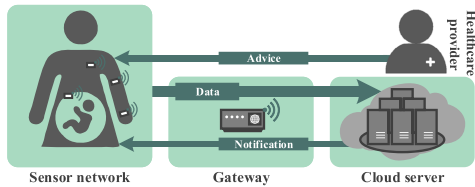


Fig. 1. An IoT-based system for remote health monitoring.

Fortunately, recent advances in Internet-of-Things (IoT) technologies have paved the way for enabling such monitoring services with 24/7 availability. IoT is a growing network of interconnected objects that envision a shared knowledge for smart and autonomous decision-making and actuation [3–6]. In the healthcare domain, IoT systems leverage different sensing, computing and communication resources.

As illustrated in Fig. 1, the architecture of IoT-based systems can be partitioned into three main tiers [7]. First, a *Sensor network* includes wearable and mobile sensors (i.e., Body Area Network) recording health and context data, by which the user's condition is perceived. Second, a *Gateway* acts as a bridge between the *Sensor network* and remote servers. Such a device (e.g., an access point) mostly performs data transmission and conventional services such as protocol conversion. However, alternative network infrastructures (e.g., smart e-health gateways) are proposed to incorporate intelligent techniques into the edge of the network [8–10]. Third, a *Cloud Server* offers broadcasting, data storage and a wide range of data analytic techniques (e.g., machine learning), through which healthcare services and applications are obtained [11].

In the real-world domain, missing data is one of the biggest challenges among the IoT-based health monitoring systems. Missing data refers to an entry in data where no value is available. Such missingness often occurs over the process of health monitoring, in particular long-term screening, due to failure in data collection and data transmission, as the sensor(s) might detach from the skin, lose connections with gateway devices or run out of batteries. Moreover, in case of long-term monitoring, the user might refuse or forget to use wearable sensor(s) all the time. This inconsistent and incomplete data collection leads to failure in decision making and consequently the mission of the application.

There is a large body of literature on the analysis of missing data in databases [12,13]. However, most of the conventional techniques are insufficient for real-time health monitoring systems since they neglect the variability of the missing data in estimations. This issue is especially significant in primary vital signs (e.g., heart rate) as the variations are considerably large, influenced by different factors such as health conditions, physical activities and surrounding environment. Clearly, these techniques generate biased estimates and subsequently cause high error rates in health applications. In consequence, a missing data resilient method is required to consider a wide range of parameters while minimizing the bias of estimates. We believe such a solution can be realized for real-time health monitoring systems by holistically leveraging IoT-enabled concepts such as multi-modal data collection and personalization.

In this paper, we present a personalized missing data resilient decision-making approach to continuously deliver health decisions despite missing values. This approach uses a Multiple Imputation method [12,13] reinforced with various data resources (e.g., context information) in IoT-based systems to estimate missing values. Subsequently, a personalized pooling method is introduced to provide an acceptable decision according to states

of the user and monitoring system. Our approach is proposed for a real human subject trial on maternal health where 20 pregnant women were remotely monitored for 7 months (i.e., 6 months of pregnancy and 1 month postpartum) beside normal check-up visits in maternal health clinics. In this case study, we concentrate on a real-time health application, in which maternal health status is remotely estimated using maternal heart rates. Major contributions of this paper are as follow:

- A personalized missing data resilient decision-making approach is proposed to continuously deliver health decisions despite missing data.
- The approach is presented for a real human subject trial on maternal health, focusing on a real-time health application where maternal health statuses are remotely estimated.
- Personalized models are defined and used exploiting maternal (medical) history and context data to impute the missing values.
- A personalized pooling method is introduced to fuse the values and deliver health decisions leveraging user's data.
- The proposed approach is evaluated in terms of accuracy of the health decisions, in comparison to existing missing data analysis methods.

The remainder of the paper is organized as follow. In Section 2, we outline background and related work of this research. Section 3 describes the proposed solution. The demonstration and evaluation are provided in Section 4; and finally, Section 5 concludes the paper.

## 2. Background and related work

In this section, we first present our case study on maternal health monitoring, including a maternal health indicator to remotely estimate health conditions of pregnant women. Then, we delve into the missing data concept and possible techniques of dealing with this issue.

### 2.1. Maternal health monitoring

The maternal body undergoes a variety of changes throughout pregnancy, particularly in the cardiovascular system. Cardiac output and compliance elevation is an example, which is reflected by different vital signs such as stroke volume and heart rate [14,15]. These changes are parts of physiological adaptations during pregnancy and are mostly normal. However, they are affected by pre-pregnancy and pregnancy conditions and complications. On the one hand, diseases and serious conditions such as maternal obesity, diabetes and depression considerably impact pregnancy and elevate vital signs (e.g., heart rate and blood pressure), increasing risk factors for various health problems in the mothers and their future offspring. On the other hand, a healthy lifestyle consisting of an adequate diet and regular physical activity engagement could be beneficial [16,17].

To investigate such physiological changes in pregnancy, long-term monitoring and studies of pregnant women are desirable [18, 19], assessing their health conditions and providing efficient recommendations and guidelines. In this context, we conduct a real-time maternal monitoring and concentrate on heart rate variation and physical activity of pregnant women. This study includes 7 months monitoring of 20 pregnant women, in which heart rate, steps, hand movements, sleep level and ascending/descending stairs are continuously collected via a smart wristband. The parameters should be mapped into an abstracted level of data (i.e., a health score) to continuously and explicitly indicate her maternal health status.

Therefore, a maternal health indicator is selected to remotely estimate the health condition while the user is engaging in various physical activities in everyday settings. This indicator leverages a set of guidelines, rules and recommendations that state the target ranges of heart rate in different phases of pregnancy [14, 16, 17, 20–22]. In our case study, this rule-based indicator tailors continuous monitoring of heart rate, physical activity, personalized data (e.g., baseline heart rate values at the beginning of the monitoring) and meta-data (e.g., gestational week and maternal age) to estimate the health decision. The decision is a warning sign ranging from 0 to 3, where 0 indicates a normal health condition and 3 shows the highest health deterioration [23, 24].

## 2.2. Missing data

In the first place, it is important to understand the properties and patterns of the missing values for developing effective methods in real-world applications. Various missingness mechanisms cause missing values in the health monitoring systems, interrupting real-time decision-making. As proposed by Rubin et al. [12, 13, 25], such missingness mechanisms generally stand into three main categories. (1) *Missing Completely At Random (MCAR)*. The missing value is independent of the data values. For example, unpredictable data loss occurs during the monitoring in case of sensor failure or loss of Internet connection. (2) *Missing At Random (MAR)*. The probability of data to be missing is related to available information. However, the missingness does not depend on the missing values. For instance, the vital signs are more likely to be missing in the evening, as the sensors are disconnected to be charged when the user is at home. (3) *Not Missing At Random (NMAR)*. It occurs when the missingness depends on the missing values. For example, a pregnant woman removes the wearable devices while she is smoking, obscuring the direct effect of smoking on the vital signs.

There is a broad variety of missing data analysis methods in the literature, aiming to provide estimates with acceptable bias (i.e., distance between the estimate and the true value) for missing values [13, 26–29]. Such analysis methods have their own strengths and restrictions. They are selected according to target applications with different requirements (e.g., desired accuracy) and limitations (e.g., the amount of missing data and the missingness mechanisms). In the following, we outline various missing data analysis methods available in the literature.

Deletion methods are the most straightforward approaches for handling missing data, where records with missing values are eliminated. Listwise deletion is one of the methods where a record is dropped out from the analysis if it has at least one missing attribute. This method results in a complete dataset although it reduces the amount of data. Similarly, Pairwise deletion is another method in which a record is omitted on an analysis-by-analysis basis. This method minimizes the deletion, in contrast with the Listwise deletion, as records with missing values are kept if their under-analysis attributes are not missing. Such deletion methods are restricted to MCAR, otherwise they produce biased estimates [28, 30–32].

Despite the deletion methods, imputation-based methods fill in the missing values exploiting available (i.e., observed) data. There are different imputation methods in the literature including mean imputation, Last Observation Carried Forward (LOCF) imputation, regression imputation, hot-deck imputation, cold-deck imputation and K-Nearest-Neighbor (KNN) imputation [12, 33–35]. Unfortunately, such single imputation methods might lead to biased estimates, as they neglect the variability of the missing values. Additionally, Multiple Imputation (MI) is a modern missing data imputation method that complete the dataset, considering imputation uncertainty [12, 13, 36–38]. MI includes three

main steps as *Imputation, Analysis and Pooling*. First, different estimates ( $n \geq 2$ ) for the missing values are created via different procedures (e.g., linear regression and hot-deck). Second, the completed datasets are analyzed. Last, the results are integrated into one final output. In contrast with single imputation methods, MI is applicable for both MAR and MCAR.

In addition to the imputation-based methods, model-based methods create a model of the observed data to estimate the missingness. For example, Maximum Likelihood Estimation (MLE) method utilizes available data to approximate parameters (e.g., mean and standard deviation of a log-likelihood function) that fits the data [13, 39, 40]. Missing values can be estimated via the obtained model. MLE provides unbiased estimates for MAR and MCAR. Furthermore, there are model-based methods such as pattern-mixture, selection models and shared-parameter models, that are able to yield estimates for NMAR. Such methods are appropriate for studies where data are recorded repeatedly through time [41–44].

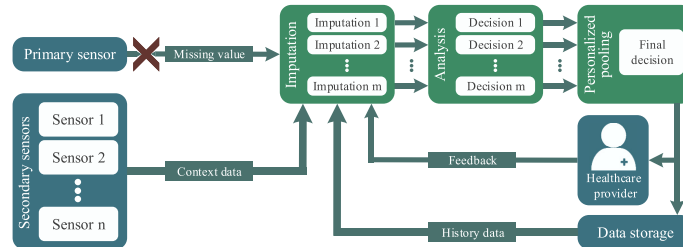
Moreover, machine learning-based methods tailor available data (i.e., attributes) to provide a hypothesis (i.e., classifier). The hypothesis could assign new values to missing attributes. Thus far, different approaches including Artificial Neural Networks (ANN), Support Vector Machine (SVM) and Generic algorithms have been evaluated for missing data estimations [45–50]. On the other hand, some machine learning-based methods handle missingness in a dataset without imputing values. In such methods, a classifier is trained by observed data including missing values, and subsequently decision making is performed. However, the missingness and poor correlation between available attributes might decrease the performance of the methods. These learning-based methods (e.g., Decision Tree) have been investigated in different studies [51–54].

In addition, there are studies to investigate missing data in IoT devices and wireless sensor network, featuring a multi-sensors data collection. In this regard, a probabilistic method has been proposed to estimate the missing value considering similarity in neighboring sensors data [55]. Similarly, missing, corrupted and late-reading data has been tackled in streaming data [56–58].

## 3. Missing data resilient decision-making approach

In this section, we tackle the missing data issue in IoT-based health monitoring systems, which are incapable of providing services when sensory data are unavailable or unreliable. In this regard, we, first, outline which missing data analysis techniques can be suitable for these systems. Then, we present the definitions and functions of our personalized decision-making approach via a case-study on maternal health monitoring.

As mentioned in Section 2.2, there is a wide range of methods available for missing data estimations, targeting different applications and missingness mechanisms. Many of the available techniques are, nevertheless, inappropriate for real-time decision-making of IoT-based health monitoring systems. Deletion methods are not applicable in such systems as the decision making is interrupted while there is a missing input. Moreover, the decision making is vulnerable to biased values when single imputation methods are exploited. LOCF imputation is also a straightforward method used for longitudinal studies, which fills in missing values leveraging the pattern of gradual changes in observed data. This method is inappropriate, due to underestimating the variation of the missing values. In addition, conventional multiple imputation, model-based methods (e.g., Maximum Likelihood Estimation) and machine learning-based methods are other possible alternatives. In health monitoring systems, these methods are insufficient for data with high variations such as heart rate, which highly depends on different factors.



**Fig. 2.** Health decision making while the primary data (from primary sensor) is missing. In this setup, context data (from Sensor 1 to Sensor  $n$ ), history data and user's feedback are utilized in the computation.

In contrast, auxiliary information can be utilized in missing data analysis techniques to mitigate the bias of the estimates [59–62]. Auxiliary information is additional data or meta-data that correlates with the value of interest (i.e., missing value). The use of such information in a missing data analysis technique is suitable for IoT-based monitoring systems due to their capability of heterogeneous data collection. Moreover, this information is very promising in real-time health decision-making as the missingness mechanism might be MAR or NMAR.

The IoT-based systems provide a great opportunity to record such auxiliary information, also named as context, along with the primary data collection throughout the monitoring. Context is the information that describes the environment and condition of the system [63]. Context-awareness in computing enables the IoT-based systems to observe and understand the sensory data and to be aware of their own states and surrounding environment, providing robust and adaptive behavior in different conditions [64, 65]. In addition, other meta-data such as medical records and user feedback can be manually added to the computations to improve the system's performance.

To incorporate context-awareness into our missing data resilient decision-making approach, we believe that Multiple Imputation (MI) method can be an appropriate alternative. In this regard, the computation of this decision-making approach is partitioned into three main components as *Imputation*, *Analysis* and *Personalized Pooling*, estimating a real-time health score while the sensory data is missing. This function is depicted in Fig. 2, where the data collected from one sensor is missing. In the rest of this paper, we entitle this sensor as primary sensor and its data as primary data; and other sensors are named as secondary sensors which acquire context data and other information including other vital signs.

We thoroughly present these three components in the following and clarify the definitions and functions of our approach via a case study on maternal health during pregnancy. In this context, we concentrate on a maternal health indicator (see Section 2.1) which remotely estimates the degree of maternal health condition while the pregnant woman is engaging in various physical activities in everyday settings. This indicator tailors sensory data and meta-data to estimate the health score (i.e., warning sign). However, its functionality is limited to the availability of the real-time heart rate value (i.e., primary data). The proposed decision-making approach allows this health indicator to acceptably operate even if the heart rate is missed due to interruptions in data collection or data transmission.

### 3.1. Imputation

A number of different methods are exploited to impute the missing value (i.e. maternal heart rate in our case)  $m$  times, where

$m \geq 2$ . Therefore,  $m$  values are estimated leveraging different resources, each of which holds a considerable correlation with the primary data that is missing. The method of selection depends on the nature of the data and the type of auxiliary information. In the following, we outline methods to impute maternal heart rate values throughout the monitoring.

#### 3.1.1. Short-term data

First, short-term history of data (i.e., preceding neighbors) can be utilized for the data imputation. These values correlate strongly with the missing value, particularly when the context situation and the individual condition are constant. Autoregressive models [66] are conventionally used for such a sequence of data, in which the current value is estimated from  $n$  preceding values. The autoregressive model of order  $n$  is defined as:

$$x_t = f_s(t, \beta) = \beta_0 + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \dots + \beta_n x_{t-n} \quad (1)$$

where  $x_{t-1}, x_{t-2}, \dots, x_{t-n}$  are the previous  $n$  data, and  $\beta_0, \beta_1, \dots, \beta_n$  are the parameters of the model estimated.

In our case study, non-missing heart rate values from previous weeks are selected as the training data to estimate the parameters via a regularized least-square (i.e., ridge regression) desired to minimize:

$$\sum_{i=1}^k [x_i - f_s(t, \beta)]^2 + \lambda \sum_{j=0}^n \beta_j^2$$

where  $k$  is the number of training data,  $x_i$  indicates the actual heart rate,  $f_s(\cdot)$  estimates the heart rate from preceding data, and  $\lambda > 0$  is a regularization parameter [67,68]. The model is periodically updated to consider variation of maternal heart rate throughout pregnancy.

The estimated value is added to the heart rate set, so it is considered as a preceding neighbor for the next iteration. When a considerable number of data items are missing, the estimates become unreliable in this imputation as the errors are accumulated. Root-mean-square error (RMSE) of the heart rate estimates for a pregnant woman is shown in Fig. 3. As indicated, the RMSE values increase when a large portion of data is missing. In a similar manner using neighboring heart rate values, the unreliability of heart rate estimation when the missing window is large is investigated in [69]. In consequence, this imputation is appropriate only when the amount of missing data is small.

#### 3.1.2. Context data

Associations between the primary data and context information can be exploited to impute the missing values. This can be indicated as:

$$x = f_c(t, \gamma) \quad (2)$$

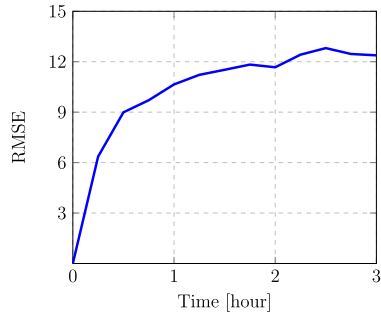


Fig. 3. RMSE of the estimates of a pregnant woman's heart rate (1714 iterations) using the autoregressive model.

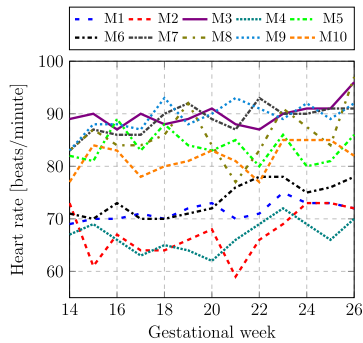


Fig. 4. Weekly average of maternal heart rate values of 10 pregnant women during sedentary time in the second trimester.

where  $\gamma$  is the context-related data and  $f_c(\cdot)$  is the function that approximates the heart rate value. In our case study, context data are the maternal physical activities, including 7 states as light sleep, deep sleep, sedentary, very light activity, light activity, moderate activity and vigorous activity. They are specified via steps and hand movements of the user [70,71]. Such physical activities are associated with the heart rate values and their variations.

However, this association is specific for each individual, so a personalized model is required. To show the differences in maternal heart rate, we select data from 10 pregnant women as examples. Weekly average heart rate values of these women during the sedentary time in the second trimester (i.e., gestational weeks 14–26) are illustrated in Fig. 4. As indicated, the heart rate ranges are not overlapped in some cases. Average heart rates of M4 vary from 62 to 72 beats/min although M3 average heart rates are between 87 and 96 beats/min. Moreover, such a model should be dynamically updated frequently (e.g., every week or every two weeks) because conditions of each pregnant woman are changing as the pregnancy advances. Fig. 5 illustrates such variations in average heart rates of one pregnant woman in different activities from gestational week 14 to postpartum week 4.

In our context, Eq. (2) can be defined as:

$$x = \gamma(t)^T H \quad (3)$$

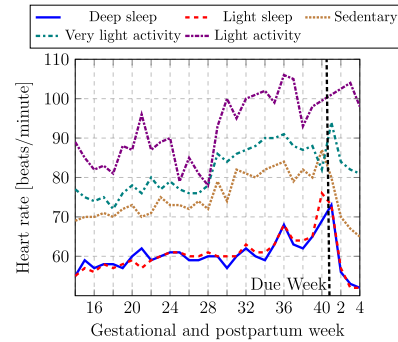


Fig. 5. Weekly average of maternal heart rate values of a pregnant woman in different activities from week 14 to postpartum week 4.

where  $\gamma(t) = [p_1(t), p_2(t), \dots, p_7(t)]$  represents which of the 7 physical activities is allocated to  $t$ , where  $p_k(\cdot)$  is either 0 or 1 and:

$$p_1(t) + p_2(t) + \dots + p_7(t) = 1$$

$H = [h_1, h_2, \dots, h_7]$  also indicates the most probable heart rate value in each state. This vector is uniquely defined for each individual according to non-missing data of previous weeks of monitoring.

### 3.1.3. Lifestyle data

Similarity in heart rate patterns due to repetitive habits (i.e., user's lifestyle) is another resource to impute missing values. These patterns could be manually added by users (feedback) or automatically extracted from the data. This is significant in the monitoring particularly when the context data is incomplete or not fine-grained enough. For example, we access to the physical activity of the pregnant women, but no information is available regarding eating and drinking habits (e.g., time and duration of meals), which affect user's heart rates [72]. With this intention, the missing value can be obtained via a function as:

$$x = f(\phi) \quad (4)$$

where  $\phi$  holds history data and/or feedback.

In our case, non-missing heart rate values of the current time window are compared with previous time windows, and the window with the most similar heart rate pattern is extracted. Then, the imputation is fulfilled using heart rates of the most similar window. In this regard, Eq. (4) can be determined as:

$$x = x_k \quad (5)$$

where  $x_k$  is the corresponding heart rate value of the window  $k$ , which has the least distance to the current window. Hence,  $k$  is specified via:

$$\operatorname{argmin}_{k \in \phi} \operatorname{dist}(k)$$

which  $\operatorname{dist}(\cdot)$  is a distance function defined as:

$$\operatorname{dist}(k) = \sum_{i=1}^n \|x_{i0} - x_{ik}\|^2$$

where  $n$  is the window length, and  $x_{i0}$  and  $x_{ik}$  are available heart rate values in the current window and window  $k$ , respectively.

Moreover, additional information can be manually collected to select the most similar heart rate pattern. Such information includes self-reported physical activities or events marked in user's

calendar, from which similar windows are selected to perform data imputation. For instance, the user participates in a certain exercise course every odd day from 2 pm to 4 pm. Heart rate data of this exercise can be leveraged if the heart rate value is missed in this activity in the future.

### 3.2. Analysis

The rule-based maternal health indicator is implemented, mapping the sensor data into an abstracted decision. It repeats  $m$  times per iteration, as  $m$  versions of the missing value are estimated in the *Imputation* part. Therefore,  $m$  decisions are generated in each iteration.  $m$  equals to 3 in our case study as the missing heart rate value is filled via the 3 imputation methods. However, the decisions might be diverse due to inaccuracy and uncertainty in the imputation methods.

The rule-based indicator generates a warning score between 0 and 3 for each heart rate value. Similar to a typical obstetric Early Warning Score (EWS) [23,24], different ranges are defined for the heart rate value to obtain the score. The ranges are defined for each pregnant woman according to personalized data such as baseline heart rate at the beginning of the monitoring. In addition, a set of guidelines and rules are utilized [14,16,17,20–22]. For examples, heart rate should not exceed 140 (beats/min) while the mother engages moderate and vigorous activities; it should not be less than 40 (beats/min) during sleep and sedentary time; and heart rate likely rises 20% till the end of pregnancy. Note that this function is assumed to indicate the functionality of the proposed approach, and it can be replaced with other classifiers.

### 3.3. Personalized pooling

A pooling method is performed to integrate the  $m$  decisions into a final decision (i.e.,  $d_{final}$ ). An arithmetic mean is a conventional method in this case. However, it might be inappropriate as the decisions with different errors are treated equally, even if some decisions hold high error rates.

We propose a *personalized pooling* method to alleviate the impact of the errors in the final decision. In this regard, a weighted arithmetic mean is exploited to pool the decisions, in which the weights become personalized throughout the monitoring leveraging user's data. In each iteration, the weights are determined and selected according to the states of the user and monitoring system. The final decision is obtained via a dot product of the vectors of the  $m$  decisions and the personalized weights that satisfies:

$$w_1 + w_2 + \dots + w_m = 1$$

When the primary data is available, the weights are calculated by the squared error between actual and estimated values. However, as conditions of the user and system are highly dynamic (e.g., state of the user and size of the missing window), general weights are insufficient, minimizing the sum of squared errors over all time points. In this regard, we define different states for each imputation and calculate the sum of squared errors over the corresponding points in each state. In the following, we outline how states and weights are defined in our case study with the 3 imputation methods.

The first imputation is related to the short-term data. The error of the imputation highly depends on the portion of missing data, as indicated in Fig. 3. Therefore, the weights should be determined for different missing window sizes. A missing window refers to the interval between the current point and the last point that heart rate data was recorded. When the missing window size is  $i$ , the last  $i$  value(s) of heart rate data including current heart rate and previous values are removed; the current

heart rate is imputed; and the weight is determined using the errors in this iteration and previous iterations. This process is repeated  $n_1$  times with different sizes of missing window, where the maximum missing window size is  $n_1$ . In consequence, a set of weights (i.e.,  $W_1 = \{w_{1,1}, \dots, w_{n_1,1}\}$ ) is obtained for the  $n_1$  missing windows.

The second imputation is associated with the context data. The uncertainty of the heart rate is significant in this imputation as the most probable heart rate is selected (see Section 3.1.2). This uncertainty (e.g., variance) are diverse in different physical activities. For instance, in most cases, the variance of deep sleep heart rate is considerably less than the variance of heart rates of vigorous activity. Therefore, the squared errors should be severally calculated for each physical activity to obtain weights—i.e.,  $W_2 = \{w_{1,2}, \dots, w_{n_2,2}\}$  where  $n_2$  is the number of physical activities. As there are 7 physical activities,  $n_2$  is 7 in this monitoring.

The third imputation is related to the lifestyle data. Meta-data including the weekly schedule of the user is considered to define different time states (i.e.,  $n_3$  states). For example, the weight for weekend-days (as a time state) is defined, considering the squared error of the time points during weekend days. In this regard, a set of weights (i.e.,  $W_3 = \{w_{1,3}, \dots, w_{n_3,3}\}$ ) is calculated for the  $n_3$  time states in the monitoring.

The three weights vectors,  $W_1$ ,  $W_2$  and  $W_3$ , are dynamically updated in iterations that the heart rate data is available. The dynamic weights determination of the *personalized pooling* method when the heart rate is available is illustrated in Fig. 6.

In contrast, in the iterations with the missing heart rate, the heart rate is imputed by the 3 imputation methods, and the health scores (i.e.,  $d_1$ ,  $d_2$  and  $d_3$ ) are calculated. The corresponding weights (i.e.,  $w_{i,1}$ ,  $w_{i,2}$  and  $w_{i,3}$ ) are selected from the three weights vectors according to the current missing data size, physical activity and time state, respectively (see Fig. 7). Finally, the health decisions are pooled using the selected weights as:

$$d_{final} = w_{i,1}.d_1 + w_{i,2}.d_2 + w_{i,3}.d_3 \quad (6)$$

Algorithm 1 also indicates the function of the *personalized pooling* when the heart rate is available and is missing.

## 4. Demonstration and evaluation

In this section, we present our case study on maternal health, where 20 pregnant women have been remotely monitored for seven months. First, we outline the study design and recruitment in this monitoring. Next, we represent the setup, data collection and data analysis in our IoT-based system. Moreover, the proposed approach is tested and evaluated by comparing the approach with conventional methods. Finally, strengths and weaknesses of the approach are discussed.

### 4.1. Study design

The monitoring was conducted on primiparous pregnant women who visited one of two maternity outpatient clinics in Southern Finland between May and September 2016. Pregnant women in Finland are provided a free of charge ultrasound examination at the end of the first trimester. The pregnant women were recruited in this appointment considering the following criteria.

1. The participant expected her first child.
2. The participant was at least 18 years old.
3. The pregnancy was singleton.
4. The pregnancy was less than 15 gestational weeks
5. The participant understood Finnish or English
6. The participant owned a PC, tablet or Smartphone to be able to synchronize the smart wristband

Consequently, twenty participants were selected as the sample size was appropriate for a pilot study [73].



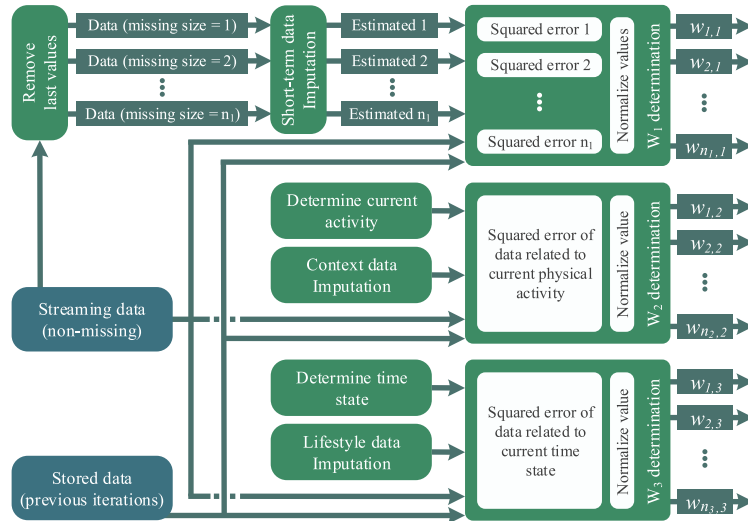


Fig. 6. The personalized pooling when heart rate is available (weights determination).

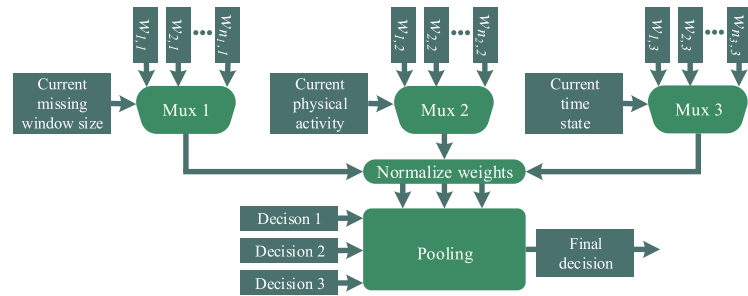


Fig. 7. The personalized pooling when heart rate is missing (weights selection).

After the ultrasound examination, the eligible women were met face-to-face once and after signing the informed consent, the device and instructions were provided. Background information was collected via a questionnaire. Some background information is represented in Table 1. Afterward, Garmin Vivosmart® HR [74] as the selected wristband for this study along with instructions has been delivered to the pregnant women. During the follow-up, the participants were interviewed via telephone.

4.2. Setup

An IoT-based system was tailored for this study, determining the Garmin wristband as the sensor device, by which physical activity and heart data were collected. The Garmin wristband is a small and light water-proof band with considerable battery life [74], so it can be an appropriate choice considering the feasibility of the monitoring. More details regarding the feasibility of this study can be found in [75].

The wristband includes one built-in optical-based sensor to record a photoplethysmogram (PPG) signal enabling real-time heart rate measurements [76]. Moreover, it consists of an inertial measurement unit (IMU) to track steps, stair ascending/descending and hand movements. In our setup, the data collection rate was set as 1 sample per 15 min, so a new data record was available in every 15 min. A 24-h sample of such data with non-missing values collected from one pregnant woman is illustrated in Fig. 8 (a,b,c,d).

The pregnant women were asked to periodically send the data to remote servers through a gateway device, which was a smartphone or a PC. Most of the data analysis was performed in the cloud servers, amalgamating sensor data to extract new information such as health status and physical activity [77]. For the data analysis, we used a Linode virtual private server (VPS) [78] with two 2.50 GHz Intel Xeon CPU (E5-2680 v3), 4 GB memory and SSD storage drive. Fig. 8 (e,f) shows such information abstracted from the data in Fig. 8 (a,b,c,d). As indicated, the health score was

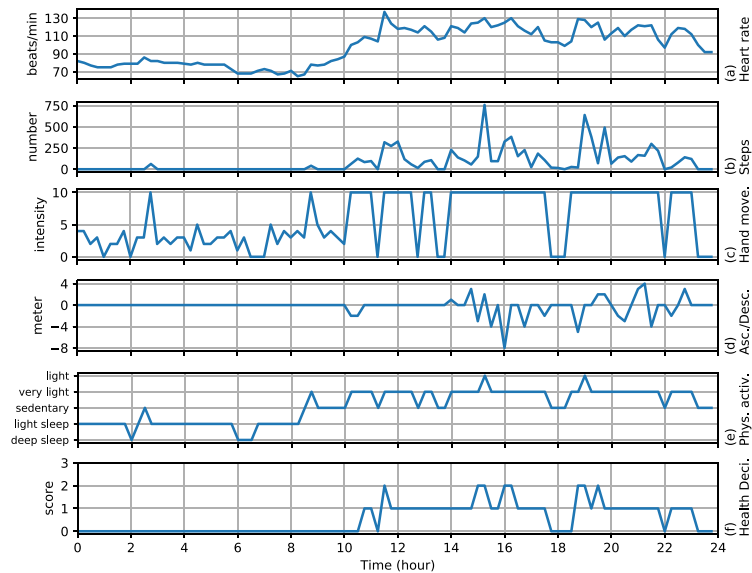
**Algorithm 1** The function of the *personalized pooling* throughout the monitoring.

```

1: Initialize:
    $n_1 \leftarrow$  maximum missing window size
    $n_2 \leftarrow$  number of physical activities
    $n_3 \leftarrow$  number of time states
    $\{w_{1,1}, \dots, w_{n_1,1}\}, \{w_{1,2}, \dots, w_{n_2,2}\}, \{w_{1,3}, \dots, w_{n_3,3}\}$ 
2: while monitoring is Active do
3:    $x_{true} \leftarrow$  data from the heart rate sensor
4:   if  $x_{true} \neq NULL$  then
5:      $d_{final} \leftarrow HealthIndicator(x_{true})$ 
6:     for  $i_1 = 1$  to  $n_1$  do
7:       remove last  $i_1$  value(s) of heart rate data
8:        $x_1 \leftarrow f_i(t, \beta)$ 
9:        $e_{1,1} \leftarrow$  squared error of the corresponding heart rate data
10:       $w_{i_1,1} \leftarrow 1 - Normalize(e_{1,1})$ 
11:    end for
12:     $i_2 \leftarrow$  determine the current physical activity
13:     $x_2 \leftarrow f_i(t, \gamma)$ 
14:     $e_{2,2} \leftarrow$  squared error of the corresponding heart rate data
15:     $w_{i_2,2} \leftarrow 1 - Normalize(e_{2,2})$ 
16:     $i_3 \leftarrow$  determine the current time state
17:     $x_3 \leftarrow f_i(t, \phi)$ 
18:     $e_{3,3} \leftarrow$  squared error of the corresponding heart rate data
19:     $w_{i_3,3} \leftarrow 1 - Normalize(e_{3,3})$ 
20:  else
21:     $x_1 \leftarrow f_i(t, \beta), x_2 \leftarrow f_i(t, \gamma), x_3 \leftarrow f_i(t, \phi)$ 
22:     $d_1, d_2, d_3 \leftarrow HealthIndicator(x_1, x_2, x_3)$ 
23:     $i_1 \leftarrow$  determine the current missing window size
24:     $i_2 \leftarrow$  determine the current physical activity
25:     $i_3 \leftarrow$  determine the current time state
26:     $Normalize(w_{i_1,1}, w_{i_2,2}, w_{i_3,3})$ 
27:     $d_{final} = w_{i_1,1}d_1 + w_{i_2,2}d_2 + w_{i_3,3}d_3$ 
28:  end if
29: end while

```

0 when the subject was sleeping. However, it varied between 0 to 2 while she engaged in different physical activities.



**Fig. 8.** A 24-h sample of (non-missing) data collected from one pregnant women in gestational week 34 (day 244th). (a), (b), (c) and (d) indicate the variables collected via the wristband; and (e) and (f) are the physical activities and health decisions calculated in the cloud server.

**Table 1** Background information of the twenty selected participants.

Statement	Type	Value
Age at pregnancy (years)	-	25.7 ± 4.96
Gestational age at recruitment (weeks)	-	12 ± 2.1
Pre-pregnancy Body Mass Index	-	25.0 ± 6.45
Quantity of pre-pregnancy physical activity in week	Once or less	3 women
	Sometimes	5 women
	Almost daily	12 women
Quality of pre-pregnancy physical activity in week	Light	8 women
	Moderate	11 women
	Vigorous	1 woman
Employment status	At work	13 women
	Student	5 women
	Unemployed	2 women
Smoking status	Pre-pregnancy	7 women
	In-pregnancy	5 women

The proposed decision-making approach was implemented with a Python service in the cloud server to estimate health status of 15 pregnant women. Five of the pregnant women were dropped out of this analysis because the missing data was too large (i.e., no data for at least 50% of the monitoring days). A view of heart rate with missing values and estimated health scores for one day of monitoring is depicted in Fig. 9. The heart rate values are missed in two time windows with lengths of 75 and 180 min. The blue circles in Fig. 9(b) are the scores when the heart rates are available; and the red triangles indicate estimated health scores while the heart rates are missing. Note that, this approach is not restricted to the cloud layer settings and can be pushed to the fog layer to enable local decision making.

In addition, manual data collection was implemented to enrich the aforementioned data collection and decision making. In this



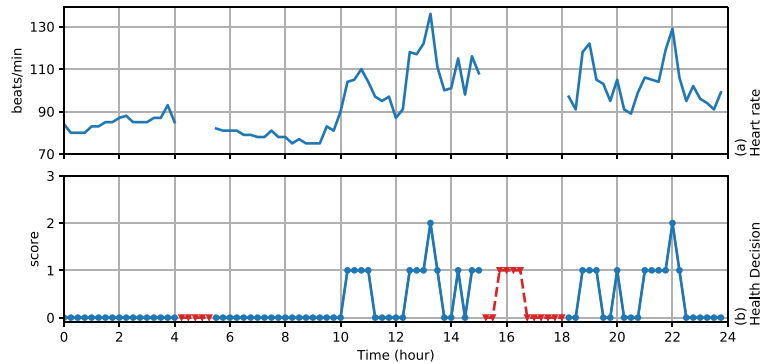


Fig. 9. A 24-h sample of heart rates with missing values and estimated health scores. The blue circles (solid line) represent the health scores obtained from the available heart rates while the red triangles (dashed line) indicate the estimated scores when heart rates are missing.

regard, semi-structured phone interviews were fulfilled once or twice in a month. Such interviews contained a set of questions to indicate the self-report physical activity on a scale 1 to 5 and certain events that considerably influence their sleep or activities. Pregnancy-related data including blood pressure, weight gain and oral glucose test were also obtained from the maternity card and hospital patient records.

#### 4.3. Ethics

The monitoring was performed in accordance with the code of ethics of the World Medical Association (Declaration of Helsinki) for experiments involving humans. Moreover, it was approved by the joint ethics committee of the hospital district of Southwest Finland (35/1801/2016) and Turku University Hospital (TYKS). In addition, the permission to employ Garmin Vivosmart® HR (Garmin Ltd, Schaffhausen, Switzerland) in this monitoring was acquired from the manufacturer Garmin Ltd.

#### 4.4. Accuracy assessment

We validate the performance of our personalized decision-making approach in terms of accuracy. In this regard, a cross-validation technique is used to discard a window of the heart rate and estimate the health score. The estimated score is compared with the actual score obtained via the actual heart rate value.

To evaluate the proposed approach, other existing methods are selected to impute missing heart rate values and extract the health scores. First, the KNN as a single imputation method is utilized, where the missing heart rate is estimated from the  $k$  preceding non-missing values by weights proportional to the inverse of the distance to the missing value. Second, the autoregressive model is used leveraging preceding neighbors. Third, the MLE as a model-based method is used, in which the missing value is extrapolated via a Sigmoid function. Fourth, the SVM (with an RBF kernel) as a machine learning-based method is tailored, imputing the missing value from the variation of the history of data (i.e., last two-weeks data). The methods are implemented using the SciPy [79] and Scikit-learn [80] libraries in Python.

In the first evaluation, we investigate the distance (i.e., RMSE) between the estimations and actual health scores with different windows of missing heart rate. The RMSE values are illustrated in Fig. 10 while the missing window (i.e.,  $x$  axis) varies from 15 min to 6 h. As indicated, when the missing window is small, the proposed method, autoregressive and KNN have the lowest

RMSE; and the RMSE values of the SVM and logistic MLE methods are higher. In contrast, in large missing windows, the RMSE values of the autoregressive and logistic MLE and KNN methods are significantly high, whereas the RMSE of the proposed method is the lowest.

In addition, we evaluate the performance of the methods by determining the C-index (i.e., concordance index) [81] of estimations in different missing windows. C-index represents how well health scores are estimated considering the correct rank/order of outcomes. In this experiment, the scores as well the outcomes are in ascending order, varying from 0, as the normal health status, to 3, as the highest health deterioration. The C-index is defined as:

$$\frac{1}{|\{(i, j) | y_i > y_j\}|} \sum_{y_i > y_j} H(\hat{y}_i - \hat{y}_j)$$

where  $y_i$  and  $\hat{y}_i$  indicate the actual and estimated decisions (i.e. scores), respectively; and  $H(\cdot)$  is the Heaviside step function.

For 15 pregnant women monitoring data, the estimation process is randomly repeated in 2040 iterations, in which the health scores are obtained considering different missing windows. Eventually, the C-index values of the 5 methods are determined. As illustrated in Fig. 11, the proposed method's C-index is approximately 0.82 when the missing window is small, and it decreases to 0.7 when the missing window is considerably large. On the contrary, C-index of SVM and logistic MLE are less than the proposed method's C-index in all cases; and the C-index of the autoregressive and KNN methods drop to less than 0.55 while the missing window is large.

#### 4.5. Discussion

The proposed approach results in more reliable and more accurate estimates compared with the conventional methods. As aforementioned, deletion methods are unfit for real-time decision making. Moreover, traditional imputation methods, model-based methods and machine learning based methods underestimate variability of the missing heart rate values, delivering estimates with high error rates. This is in accord with our findings in the previous section. In contrast, the proposed approach considers this variability in data using context information, minimizing the bias of estimates. This enhancement is particularly significant when there is a high correlation between context and the missing heart rate.

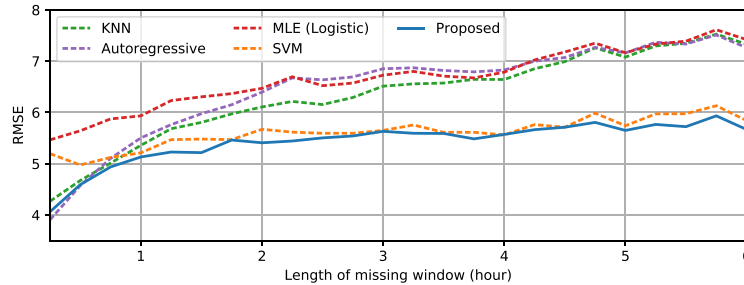


Fig. 10. RMSE values of the health scores estimations with different methods while the missing window varies from 15 min to 6 h.

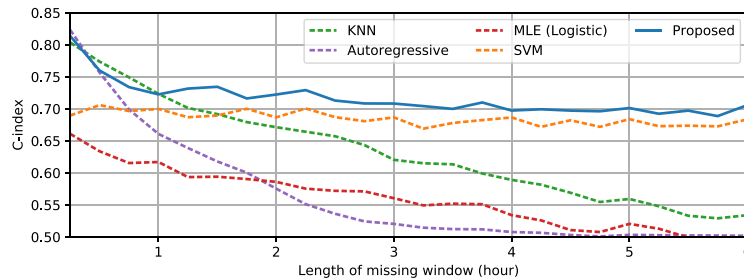


Fig. 11. C-index of the estimations with different methods while the missing window varies from 15 min to 6 h.

One of the major concern of using auxiliary information is a low correlation between context information and the missing data. As a result, the estimates could be biased, reducing the precision of the output [61]. The proposed approach mitigates such a problem in decision makings through the personalized pooling method. In this regard, a small value is allocated to the related weight when the correlation is insignificant.

Another issue in multi-sensor health IoT systems is the occurrence of missingness in more than one variable. In such cases, the *imputation* of the proposed approach is repeated  $n \times m$  times, where  $n$  is the number of missed variables and  $m$  is the number of different imputation methods for each variable. In each imputation, one missed variable is considered as the primary data, and other non-missed variables are the secondary data (i.e., auxiliary information). Next,  $n \times m$  decisions are generated, and consequently the decisions are pooled.

In addition, the proposed approach is capable of handling additions or changes in the health monitoring, adding new imputations to the approach or updating the existing imputations. This modular approach, first, suits IoT systems where the context of the user might change; and various sensors are added with respect to needs in the monitoring. Second, the approach can be distributed into the 3 layers of IoT systems (i.e., sensor network, gateway and cloud server) according to health application requirements. Moreover, adding new data resources can improve the performance of the system, removing ambiguity in the context information. This disambiguation is important when the missingness mechanism is NMAR, and the variability of missing data is invisible in available information.

Estimating health status with only one vital sign is the limitation of this study, where unexpected health deterioration with no prior history cannot be estimated when the heart rate value is missing. Therefore, the health indicator in this monitoring only

targets real-time health coaching and preventive purposes, but not health deterioration detection. However, this health indicator is a proof-of-concept for the proposed decision-making approach; and inclusion of different vital signs could alleviate this problem.

As the future work of this study, we are going to extend our work, targeting real-time health deterioration in pregnant women. We will use an obstetric Early Warning Score (EWS) [23, 24] as a standard manual tool in clinical settings to early-detect patients' health deterioration. This tool will be developed for remote health monitoring through IoT-based systems [82,83]. In this regard, five warning scores ranging from 0 to 3 are generated from five vital signs which are heart rate, body temperature, blood oxygen saturation, respiration rate and blood pressure. The aggregation of these scores represents the level of health deterioration.

## 5. Conclusion

Missing data is a prevalent problem among IoT-based health monitoring systems, where data collection and data transmission may be interrupted in long-term scenarios. This problem mostly leads to failures in decision making and subsequently health applications. Conventional missing data methods are inappropriate for such systems as these methods underestimate variability of the missing values. This is important when the vital signs such as heart rate are being missed, as heart rate variations could be considerably large. In this paper, we proposed a personalized missing data resilient decision-making approach tailoring data resources in IoT systems to enable continuous health decision making despite missing values. This approach exploited the Multiple Imputation method reinforced with auxiliary information obtained via the IoT-based system. In this regard, first, the missing values were estimated via different methods using

various resources. Second, the decision-making method was implemented, and decisions were obtained from different estimates. Eventually, the final decision was extracted using a personalized pooling method. We demonstrated the proposed approach via a real human subject trial on maternity health. The accuracy of the proposed approach was compared with existing methods. We indicated that the proposed approach leads to more accurate decisions, especially when the missing window is large.

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# Paper VI

## **Personalized Maternal Sleep Quality Assessment: An Objective IoT-based Longitudinal Study**

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# Personalized Maternal Sleep Quality Assessment: An Objective IoT-based Longitudinal Study

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**ABSTRACT** Sleep is a composite of physiological and behavioral processes that undergo substantial changes during and after pregnancy. These changes might lead to sleep disorders and adverse pregnancy outcomes. Several studies have investigated this issue; however, they were restricted to subjective measurements or short-term actigraphy methods. This is insufficient for a longitudinal maternal sleep quality evaluation. A longitudinal study: 1) requires a long-term data collection approach to acquire data from everyday routines of mothers and 2) demands a sleep quality assessment method exploiting a large volume of multivariate data to assess sleep adaptations and overall sleep quality. In this paper, we present an Internet-of-Things-based long-term monitoring system to perform an objective sleep quality assessment. We conduct longitudinal monitoring, where 20 pregnant mothers are remotely monitored for six months of pregnancy and one month postpartum. To evaluate sleep quality adaptations, we: 1) extract several sleep attributes and study their variations during the monitoring and 2) propose a semi-supervised machine learning approach to create a personalized sleep model for each subject. The model provides an abnormality score, which allows an explicit representation of the sleep quality in a clinical routine, reflecting possible sleep quality degradation with respect to her own data. Sleep data of 13 participants (out of 20) are included in our analysis, as their data are adequate for the study, including  $172.15 \pm 33.29$  days of sleep data per person. Our fine-grained objective measurements indicate that the sleep duration and sleep efficiency are deteriorated in pregnancy and notably in postpartum. In comparison to the mid of the second trimester, the sleep model indicates the increase of sleep abnormality at the end of pregnancy (2.87 times) and postpartum (5.62 times). We also show that the model enables individualized and effective care for sleep disturbances during pregnancy, as compared to a baseline method.

**INDEX TERMS** Anomaly detection, Internet of Things, longitudinal study, maternity care, sleep monitoring, sleep quality assessment.

## I. INTRODUCTION

Several physical, physiological, and hormonal adaptations occur during pregnancy to accommodate the developing fetus and to prepare the mother for the delivery [1], [2]. Such variations in the maternal body alter sleep patterns of pregnant women in many ways. In this regard, sleep disturbances are

particularly prevalent throughout the pregnancy, including various disorders to maintaining sleep (e.g., insomnia), sleep deprivation, and restless legs syndrome [3]–[6]. Moreover, sleep patterns of pregnant women might be altered in postpartum months, as they experience new life situations after labor [7].

Studies show that sleep disturbances negatively impact maternal and child health during and after pregnancy [8]. Sleep problems are associated with a high likelihood of

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poor obstetric outcomes and different diseases such as gestational diabetes, preeclampsia, and stress overload [9]–[11]. Also, they lead to increased risk of preterm birth, intrauterine growth restriction, and unplanned Caesarean deliveries [12], [13]. Moreover, different studies discussed the correlation between sleep disturbances and postpartum diseases and complications such as depression and damage to the mother-infant relationship [12], [14]. Thus, screening, monitoring, and assessment of maternal sleep quality are essential during pregnancy to alleviate sleep disturbances and prevent its potential complications [12], [15], [16].

Sleep quality is a complex concept that is traditionally evaluated via qualitative attributes (i.e., subjective measurements) and more recently via quantitative attributes (i.e., objective measurements) [17]. Subjective techniques determine perceived sleep quality by inquiring the individuals about their sleep experiences such as sleep duration and disturbances. These techniques are often performed via self-report questionnaires such as the Pittsburgh Sleep Quality Index (PSQI) [18] and Berlin Questionnaire [19]. Those are widely used in sleep quality evaluation of different groups of people as they are relatively straightforward and easy to implement for longitudinal studies. Similar subjective techniques have also been utilized for pregnant women to reveal the impact of pregnancy on maternal sleep [5], [8], [15], [16], [20]–[22]. However, such subjective methods can be inaccurate and poorly reflect sleep quality level, as the data collection is mostly limited to scheduled interviews, Internet-based surveys, or self-report questionnaires. The shortcomings and poor performance of such methods have been widely discussed in several studies investigating the validity of the subjective sleep quality assessment methods [17], [23]–[25].

Alternatively, objective techniques measure the user's physical and health conditions and translate the results into sleep attributes such as sleep efficiency and sleep stages for further assessment. Polysomnography (PSG) is a conventional test in this regard, where several bio-signals are acquired for sleep analysis [26], [27]. The PSG, as the gold standard of the sleep assessment, has been exploited for sleep disturbances monitoring in pregnancy [4]. However, it is bounded to one or a limited number of nights due to its data acquisition limits. Actigraphy is another objective method that examines sleep quality by monitoring human rest/activity cycles [28]. Data acquisition in actigraphy is more convenient and non-invasive for users, as it is performed via a small and light-weight wearable device placed on the user's wrist or ankle. Standalone (i.e., without network connectivity and real-time remote access) actigraphy monitors have been deployed for offline and short-time sleep monitoring, such as the works presented in [29]–[32] where maternal sleep is monitored for up to 14 days. However, the constraints in local storage and processing have hindered the utilization of this technology for longitudinal sleep quality monitoring.

Longitudinal objective sleep monitoring necessitates a long-term data collection to acquire data from everyday routines of participants 24/7. We believe recent advancements

in Internet-of-Things (IoT) technologies provide an unprecedented opportunity to enable such continuous health monitoring. IoT is an emerging network of interrelated objects that tailors a distinct set of paradigms such as wearable electronics, communication infrastructure, and data analytics to deliver personalized services to the end-users [33], [34]. However, it should be noted that an IoT-based sleep monitoring system, despite being a powerful tool, generates a large volume of multivariate data which dramatically increases over time. Such big data [35], while being a rich source of information, call for tailored and intelligent data analytic techniques and models.

Conventional techniques assess the sleep quality only from a single perspective by separately extracting and analyzing each sleep attribute (e.g., sleep duration) from a pool of sleep-related data. Data in a high-dimensional space require a more intelligent amalgamation method to transform all sleep attributes into a single overall sleep quality score, in a way that the contribution of each attribute is automatically considered in the final score. This allows a straightforward representation of the sleep quality in a clinical routine and reflecting possible sleep quality degradation of an individual with respect to her own life situation and health condition. We believe that such a method is particularly essential for maternal sleep quality assessment and individualized care approach, as a mother's physical and mental states undergo a process of change throughout the course of pregnancy and postpartum, which necessitates an explicit indicator of the mother's sleep changes during this period.

In this paper, we present an IoT-based long-term monitoring system that employs a wrist-worn device to assess the sleep of pregnant women during pregnancy and postpartum thoroughly. Our monitoring system is deployed on a real human subject trial where 20 pregnant women are remotely and continuously monitored for six months of pregnancy and one month postpartum. We first study sleep quality changes in this monitoring, leveraging several objective attributes. We then propose an anomaly detection approach to construct a personalized sleep model for each individual using the sleep data from the beginning of the monitoring process. We measure the sleep adaptations of the rest of the pregnancy and postpartum, using the personalized model to investigate the maternal sleep quality from a different perspective. In summary, the contribution of this paper is manifold:

- i) Presenting an IoT-based long-term monitoring system to perform objective sleep quality assessment during pregnancy and postpartum.
- ii) Conducting a longitudinal study on a human subject trial on maternal sleep.
- iii) Observing the degradation of sleep quality during pregnancy and postpartum separately for a set of fine-grained quantitative sleep attributes.
- iv) Proposing a neural network-based approach to investigate maternal sleep quality adaptations in a comprehensive and personalized way.



The rest of the paper is organized as follows. We outline the background and related work of this research in Section II. Section III describes the study design. In Section IV, we present our sleep analysis approaches. Results and findings are presented in Section V. In Section VI, we discuss our findings, evaluate the model, and represent limitations and future directions of this study. Finally, Section VII concludes the paper.

## II. BACKGROUND AND RELATED WORK

In this section, we first outline the background of maternal health and sleep monitoring. Then, we present state-of-the-art anomaly detection techniques as appropriate tools to create models for abnormality detection.

### A. MATERNAL HEALTH AND SLEEP MONITORING

Maternal health can be monitored during pregnancy to ensure the well-being of both the mother and her future child. Pregnancy is a window to a woman's future health [36], and thus women are also interested in monitoring their health during pregnancy. Furthermore, using systematic and regular monitoring, several abnormalities and complications regarding pregnancy could be detected early and be treated accordingly. Maternal health monitoring, however, varies in different countries, and only half of women receive the recommended amount of care during their pregnancy [37]. Therefore, there is a need to develop new solutions that can widen the availability of maternal health monitoring for all pregnant women.

Sleep as an important part of overall maternal health requires particular attention. Multiple hormonal and physiological changes during pregnancy might contribute to sleep problems. For example, nausea, vomiting, or anxiety might cause sleep disturbances in the first trimester of pregnancy. As pregnancy progresses, the frequency and duration of sleep disturbances increase. Frequent urination, backache, leg cramps, and anxiety about delivery are common reasons for compromised sleep in the third trimester.

Sleep disturbances are common during pregnancy and are the risk factors of adverse pregnancy outcomes such as prenatal depression, gestational diabetes, and preterm birth [11], [16], [38], [39]. Also, many women suffer from acute sleep deprivation during the postpartum period, and compromised sleep may continue even several months after birth [39]. This problem might lead to diseases such as maternal fatigue and postpartum depression [14]. It is possible to use nonpharmacological strategies such as regular physical activity, controlling weight gain, and relaxation, to alleviate sleep disorders during pregnancy. Medication should be used only in severe cases to avoid possible teratogenic effects [40]. Sleep quality assessment is the first step for managing sleep disturbances and disorders. It gives an accurate picture of sleep changes and assists to early-detect sleep problems [41]. In particular, systematic and personalized sleep assessment enables the provision of right strategies to manage sleep disturbances and disorders of each woman.

Different methods have been proposed in the literature to investigate sleep problems. The duration, as well as the quality of sleep during pregnancy, has usually been measured using questionnaires [16], [42], [43]. The Pittsburgh Sleep Quality Index (PSQI) is the gold standard for subjective sleep quality assessment, in which individuals are asked to answer a self-report questionnaire [18]. The tool discriminates "good" sleep quality from "bad" leveraging seven component scores such as sleep latency, habitual sleep efficiency, and use of sleeping medication. Such subjective methods are not accurate; pregnant women have both over and underestimated their sleep duration compared with objective measurements [44].

Polysomnography (PSG) is the gold standard of sleep monitoring. The method typically employs various wearable sensors to capture several bio-signals including electroencephalogram (EEG), electromyogram (EMG), electrooculogram (EOG), and electrocardiogram (ECG), providing different sleep indices such as sleep efficiency, sleep onset latency, and sleep stages [4], [26], [45]. However, the use of the PSG is limited to sleep laboratories and clinical settings due to the burdensome implementation of its multisensor data acquisition. Therefore, the method was mostly performed in a short period of time in sleep studies. For example, an overnight lab-based PSG was implemented along with the Berlin questionnaire, targeting obstructive sleep apnea [19]. Similarly, in the maternity care, sleep disturbance was investigated via a short-term PSG-based data collection, i.e., two consecutive nights in each trimester, and in first and third postpartum months [4].

Actigraphy is another low-cost alternative for monitoring sleep and sleep-wake behavior of an individual [28]. The Sleep actigraphy typically includes an actigraph device equipped with a 3-axis MEMS accelerometer sensor, a low-performance processor and a limited memory. The acceleration data are locally processed, and sleep parameters are extracted. The actigraphy method is easy-to-use in out-of-hospital settings in contrast to the PSG. However, it is bounded to offline services. Objective sleep monitoring has been fulfilled in different maternal studies using short-term actigraphy methods [30], [46]. For example, Lee and Gay [29] investigated the association between sleep disturbance in late pregnancy with labor using an actigraphy for 2 days along with subjective measurements in the ninth month of pregnancy; a seven-day actigraphy and PSQI methods were employed for maternal sleep disturbance [31]; and Haney *et al.* [32] assess sleep in early pregnancy exploiting a 14-day actigraphy method, questionnaires, and blood pressure measurements.

Contact-free sensors have also been proposed for sleep monitoring. Some examples are visual-based sensors [47], mattress-based sensors [48], and smartphone sensors [49]. They were mostly designed to acquire sleep patterns as well as vital signs such as heart rate and respiration rate. The use of such systems has been limited in real-world applications because of restrictions in data collection and high cost. In one

study, the maternal body movements of 2 pregnant women were monitored for a couple of weeks, using a piezoelectric sensor board placed beneath their mattress [50].

### B. ANOMALY DETECTION

Anomaly detection, also known as outlier detection, is the problem of finding patterns or events in data that differ from the expected behavior [51]. Anomaly detection has been applied in many fields including fraud detection, healthcare, and intrusion detection in cybersecurity [52]. An anomaly detection technique applied to a problem depends on a variety of factors including the availability of labeled data, the nature of the data, the type of anomalies to be detected, the output of the method, and in some cases the field of study.

The type of anomalies in a dataset can be divided into three major categories [51]. First, *point anomalies* refer to data instances that are anomalous with respect to the rest of the data (i.e., normal data). Second, *contextual anomalies* are data instances that are anomalous in a certain context. For example, 150 heart beats per minute would be normal during exercise although it is anomalous if the user is sleeping. Third, *collective anomalies* refer to a group of related data instances which together are considered anomalous. For instance, recording a couple of high heart rate events in a day would be detected as anomalous (e.g., health deterioration) in a health application. Moreover, datasets can be modified to change the anomaly type; e.g., *point anomalies* and *collective anomalies* can become *contextual anomalies* if we add context information to the dataset.

The choice of a specific anomaly detection method – *supervised*, *semi-supervised*, and *unsupervised* – is greatly dependent on the type of data involved. The data can generally be divided into binary, categorical, or continuous. However, it can be a combination of these categories in some cases. In addition, the output of the method can be either binary (i.e., normal or anomalous) or continuous in the form of an anomaly score which represents the degree of the anomaly [51]. The availability of labeled data is a common challenge in anomaly detection, as anomalies might not occur frequently. Moreover, labeling of a dataset by an expert is time-consuming and expensive. The extent of the availability of a labeled dataset determines which method is used.

*Supervised* anomaly detection methods rely on data with labels for both the normal and anomalous classes. They construct a predictive model to differentiate normal and abnormal behavior. However, unbalanced distribution of data should be considered in such models, as in practice anomalous data do not occur as often as normal data. Examples of such methods include Neural Networks methods [53], Support Vector Machine (SVM) [54], and Rule-based approaches (e.g. Decision trees) [55].

*Semi-supervised* anomaly detection methods deploy semi-supervised learning (also known as one-class learning methods) that only consider normal data to train their models. When the model is created to understand normal behavior, it can then distinguish between normal and

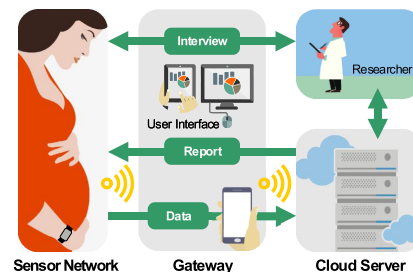


FIGURE 1. The IoT-based system for the maternal health monitoring.

anomalous classes. These methods are commonly applied because of unavailability or shortage of anomalous data in many applications. Moreover, no data labeling is required, as all the input data are normal. Some examples of these methods are Statistical techniques [56], one-class Support Vector Machine (SVM) [57], and Neural Networks methods [58]–[60].

In contrast, *unsupervised* anomaly detection methods deploy unsupervised learning techniques that require no training data, assuming the normal data occur more often than anomalous data. Unfortunately, applying data that do not fit this assumption would lead to a high false positive rate. Clustering techniques [61] and Nearest Neighbor techniques [62] are examples of unsupervised or semi-supervised techniques, which rely on the assumption that normal data remain in a cluster or dense neighborhood while anomalous data do not. They often require large training data for the normal classes.

### III. STUDY DESIGN

This paper proposes an IoT-based monitoring system equipped with a semi-supervised machine learning approach, by which pregnant women can be monitored remotely, continuously, and long-term. Also, the proposed system enables personalized sleep analysis during pregnancy and the postpartum, providing effective care for maternal sleep disturbances. We present this system for a real human subject trial on maternal sleep, where pregnant women are monitored in six months of pregnancy and one month postpartum. In this section, we introduce the IoT-based monitoring system and provide details about our implementation setup, the participants, and recruitment.

#### A. IOT-BASED MONITORING SYSTEM

An IoT-based system is introduced to continuously monitor the pregnant women. As shown in Figure 1, the architecture of the proposed system is partitioned into three main tiers. First, the sensor network performs data collection in IoT-based systems, located in the vicinity of the end-users. It acquires pregnancy- and sleep-related data from the end-users constantly. Thanks to the advances in embedded and wearable technologies, various lightweight energy-efficient wearable devices such as smartwatches, fitness trackers and Holter monitors are nowadays available for this tier.

The gateway, as the second tier, is a bridge between the sensor network and the Internet (i.e., cloud servers). The gateway is responsible for data transmission and protocol conversion. Smartphones and tablets as widespread mobile computing devices can be employed in this layer. They provide data transmission in both directions, transmitting collected health data to the cloud servers as well as sending reports and feedback to the end-user. Moreover, subjective measurements including interviews and Internet-based surveys can be carried out.

The cloud server, as the third tier, includes a high-performance computing infrastructure. It is responsible for the sleep quality analysis (e.g., data abstraction and modeling). Our semi-supervised machine learning approach is fully positioned at this tier. Moreover, the cloud server manages, secures, and stores the data remotely and is capable of providing a control panel for data visualization. The processed data are shared with the experts (e.g., researchers) for further analysis.

**Setup:** For the data collection, we restricted our selection of sensor nodes to wearable products (e.g., smart wristbands and smartwatches) that are technically applicable and practically feasible to continuous long-term monitoring [63]. Various studies have shown the validity and reliability of such wearables in terms of sleep parameters by comparing different wearables with the gold standard PSG [64]–[66]. At the beginning of the study, various devices such as Garmin Vivosmart HR [67], Microsoft Band<sup>1</sup> and Fitbit Charge HR<sup>2</sup> were available in the market. We selected the Garmin Vivosmart HR considering several factors such as the built-in sensors, battery life, small size, light weight, strap design, and waterproofness. More details of the feasibility of this study can be found in [68].

The Garmin Vivosmart HR contains an optical sensor and an inertial measurement unit (IMU), through which photoplethysmogram (PPG) [69] and acceleration signals are collected. In our setup, the participants were requested to wear the device continuously. We acquired a set of data every 15 minutes, including heart rate, step counts, and body movements. The data were utilized for the sleep analysis.

In addition, the pregnant women were asked to frequently synchronize the wristband's data with the remote servers via gateway devices – their smartphones or personal computers in this setup. For the server, we used a Linode virtual private server (VPS) [70] with two 2.50GHz Intel Xeon CPU (E5-2680 v3), 4GB memory, and SSD storage drive. The cloud server was used to store the data remotely, to perform the sleep quality analysis methods, and to provide data visualization.

## B. PARTICIPANTS AND RECRUITMENT

The monitoring was performed on primiparous pregnant women attending to one of two selected maternity

<sup>1</sup><https://support.microsoft.com/en-us/help/4000514/band-2-get-started>

<sup>2</sup><https://www.fitbit.com/be/chargehr>

TABLE 1. Background information of the selected participants.

Statement	Type	Value
Age at pregnancy (years)	–	25.7 ± 4.9
Pre-pregnancy BMI	–	25.0 ± 6.4
Quantity of pre-pregnancy physical activity in week	Once or less	3 women
	Sometimes	5 women
	Almost daily	12 women
Quality of pre-pregnancy physical activity in week	Light	8 women
	Moderate	11 women
	Vigorous	1 woman
Employment Status	At work	13 women
	Student	5 women
	Unemployed	2 women
Marital Status	Married or with partner	17 women
	Single	3 women
Educational Status	Below secondary education	4 women
	Secondary education	9 women
	College	4 women
	University	3 women
Smoking Status	Pre-pregnancy	7 women
	In-pregnancy	5 women

outpatient clinics in Southern Finland Between May 2016 and June 2017. Practically, all pregnant women in Finland visit a public health nurse regularly in a maternal health clinic. They may also participate in a free of charge ultrasound examination at the end of first trimester. The participants of this study were recruited in this examination satisfying certain criteria:

- 1) The participant is at least 18 years old.
- 2) She should expect her first child.
- 3) The pregnancy is singleton.
- 4) The gestational age should be less than 15 weeks.
- 5) She understands Finnish or English.
- 6) She owns a smartphone, tablet, or personal computer.

Twenty-two pregnant women who met the criteria were informed after the ultrasound examination. Based on this initial interest, the procedure and purpose of the study were provided for the women with phone calls. Twenty women agreed to participate in the study. In face-to-face meetings, the researchers collected background information of the participants, some of which presented in Table 1. Afterward, the wearable devices and instructions were delivered to the participants.

## C. ETHICS

The study was conducted in accordance with the code of ethics of the World Medical Association (Declaration of Helsinki) for involving human subjects in the experiments. It was also approved by the joint ethics committee of the hospital district of Southwest Finland (35/1801/2016) and Turku University Hospital (TYKS). Moreover, the written informed consent was obtained from all participants enrolled. In addition, the permission to use Garmin Vivosmart® HR (Garmin Ltd, Schaffhausen, Switzerland) in this study was acquired from the manufacturer Garmin Ltd.

#### IV. SLEEP QUALITY ANALYSIS

In this section, we present our sleep quality analysis approach tailored for assessment of maternal sleep adaptations during pregnancy and postpartum. From the collected data, we first extract several sleep attributes, each of which focuses on a specific aspect of sleep quality. Changes and trends of these attributes are explored for each subject throughout the monitoring process. We then propose a personalized sleep model for each subject to assess sleep quality in a comprehensive and personalized way. The personalized model is constructed by feeding the sleep attributes from the early stages of the monitoring to a machine learning approach.

##### A. SLEEP ATTRIBUTES

Various objective sleep attributes have been proposed in the literature for sleep quality assessment at many levels [71]. The selection of these attributes depends on the type of collected data (i.e., bio-signals and acceleration data) and subsequently the level of the analysis. For example, actigraphy can be used to extract sleep quantity parameters such as sleep duration and awake after sleep onset [72], [73]. On the other hand, EEG, EOG, and respiration signals are utilized to obtain attributes related to the sleep stages (e.g., REM sleep) [74]. In this study, a wristband equipped with PPG and IMU sensors is employed to continuously collect different parameters such as physical activity, body movements, and heart rates. We exploit these parameters to extract conventional sleep quantity, quality, and schedule attributes [17], [23], [71], [75]. In this regard, eight objective sleep attributes are extracted from each sleep event during nighttime to investigate maternal sleep adaptations. The attributes are outlined as follows:

- *Sleep Duration*, also known as Total Sleep Time (TST), indicates the total time that a user sleeps in a day [76]. It is one of the prevalent parameters in sleep analysis, widely used as a predictor of illnesses and mortality. The association between short/long sleep duration and high risks of different diseases such as cardiovascular diseases, stroke, and hypertension is demonstrated in the literature [77], [78]. In this study, the sleep duration is extracted using sleep information (i.e., start and end of the sleep) provided by the Garmin Vivosmart HR. To validate the sleep information, we implemented a manual cross-check between the sleep information and other data such as body movements and heart rates. The sleep information is corrected or discarded if there was no match between the data. Note that a Listwise deletion method is used to eliminate sleep events including missing values [79]. We also excluded short naps in the analysis, due to the limitations of our study.
- *Sleep Onset Latency (SOL)* refers to the amount of time that a user spends in bed before her status changes to the sleep state [80]. In this study, the sleep onset latency is obtained using the step counts data, and body movements and orientations. It is the time between the

occurrence of the last step before the sleep event and the beginning of the sleep event.

- *Wake After Sleep Onset (WASO)* refers to the amount of time that a user is awake after the sleep has begun and before the final awakening [80]. In this study, we use body movements and orientations data to determine the WASO during the sleep event. Step counts data are also used to detect if the user leaves the bed.
- *Sleep Fragmentation* indicates the number of awakenings that occur after the sleep is initiated and before the final awakening [81]. In this study, the sleep fragmentation is also obtained using the body movements and step counts data, by counting the times the user wakes or leaves the bed during the sleep event.
- *Sleep Efficiency* is the ratio of the time that the user is sleeping (i.e., sleep duration) to the total time spent in bed [4]. In this study, the bedtime is determined using the step counts data. It is considered as the time between the occurrence of the last step before the sleep event and the first step after the sleep event. The sleep efficiency is calculated as sleep duration divided by bedtime.
- *Sleep Depth* reflects the ratio of deep sleep duration (i.e., motionless sleep) to the amount of time of total sleep (i.e., sleep duration). Conventionally, the sleep stages including non-REM (i.e., N1, N2, N3, and N4 stages) and REM sleep are measured via Polysomnography tests utilizing EEG, EMG, and EOG signals [82], [83]. However, due to limitations of the data collection in this long-term monitoring, these sleep stages cannot be distinguished. In this study, this attribute is defined according to the body movements data, showing the amount of motionless sleep in total sleep period, which likely reflects deep sleep (i.e., N3 and N4 stages).
- *Resting Heart Rate* refers to the number of heart beats per minute when the user is at complete rest. As a cardiovascular risk factor, this attribute was investigated in studies, tackling associations between elevated resting heart rate and increased risk of cardiovascular diseases and mortality [84], [85]. In this study, we define this attribute for each sleep period by calculating the minimum value of total sleep heart rates.
- *Heart Rate Recovery* is the time between the start of the sleep and the time when the resting heart rate is reached. This attribute can be considered as a readiness score of the user. In this study, heart rate recovery is obtained using sleep event and resting heart rate information.

##### B. PERSONALIZED SLEEP MODEL

We propose a personalized sleep model to investigate sleep quality adaptations in pregnancy and postpartum. The model is trained via the user's sleep data at the beginning of the monitoring. Then, the model is used to evaluate the changes and trends of data from the rest of the monitoring (i.e., test data). The test data instances are affected by the new life conditions of pregnancy; and as the model output, a score is desirable that is indicative of the degree of the sleep abnormality.

The personalized models for sleep can leverage anomaly detection methods for identifying such abnormalities and outliers in a dataset. We delve into state-of-the-art anomaly detection methods and develop a suitable method for maternal sleep quality assessment. As mentioned in Section II-B, there is a broad range of methods for anomaly detection. However, many of them are inappropriate for our study.

In this monitoring scheme, a data instance or sleep event is multivariate (i.e., multiple attributes), and no contextual or behavioral data is included. Therefore, we only focus on *Point Anomalies* approaches where a data instance can be selected as anomalous with respect to the rest of the data instances, but not the context information. Moreover, the proposed technique should create a model using the “normal” data. Therefore, our selection is narrowed down to semi-supervised anomaly detection techniques.

Considering the output produced by the anomaly detection, binary techniques are not applicable in this study because they assign a binary label (i.e., normal or abnormal) to the test instance. Support vector machine-based methods are examples of binary techniques. Also, rule-based techniques generally require training data to contain labels for both normal and anomalous classes [55]. Moreover, Nearest Neighbor techniques (e.g., KNN) use a distance between a test data instance and its nearest neighbors to determine if it is anomalous. However, their performance highly depends on the size of the training data and dimensionality of the features. Clustering techniques are difficult to apply when the training data is small because there is a high tendency for the anomalous class to form a large cluster leading to a high false positive rate [61]. Statistical techniques present alternatives that rely on the assumptions (i.e., statistical models) made about the data generating distribution. They are also inappropriate since the assumptions tend not to hold true in high-dimensional data (like our dataset) and cannot capture interactions between features [51].

In contrast, artificial neural networks have been successfully applied to anomaly detection in various fields [53], [58], [86]. Replicator Neural Networks (RNN), also known as Auto-encoders, are the most commonly used form of neural networks in semi-supervised and unsupervised settings [58], [86], [87]. They are known for their ability to work well with high dimensional datasets and to capture linear and nonlinear interactions in the data. However, these techniques might show poor performance when the training data size is small.

Bayesian networks-based methods tackle this issue, including probability distributions in their models. They provide an uncertainty estimate along with the output, where it serves as a confidence bound on the output of the model. In addition, the model performs efficiently in case of small data instances and is robust to over-fitting [88]. This quality is important in this study, as we have a limited amount of data samples (i.e., sleep events for each participant) to train an individualized sleep model. Integrating a Bayesian method into artificial neural networks was first proposed by

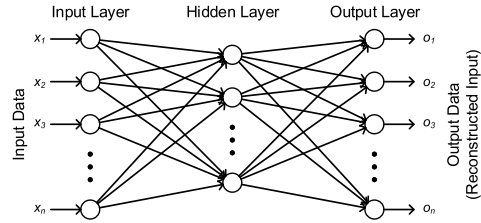


FIGURE 2. Replicator neural network with one hidden layer.

MacKay [89] and Neal [90]. This technique has been applied in several domains including medical diagnostics and Internet traffic classification [91].

We exploit the same concept to construct the personalized sleep model, incorporating a Bayesian approach into a Replicator Neural Networks (RNN).

RNN was first proposed by Hawkins *et al.* [59] and has been further developed by Dau *et al.* [60]. The method belongs to the class of auto-associative Neural Networks with compressed internal representations [60]. It captures a nonlinear representation of the input data and attempts to reproduce the input data as the output of the network. During the training process, the weights in the network are optimized to minimize reconstruction errors of the training data. For a given data instance ( $i$ ), the reconstruction error is defined as:

$$\delta_i = \frac{1}{n} \sum_{j=1}^n (x_{ij} - o_{ij})^2 \quad (1)$$

where  $n$  is the number of features in the data instance,  $x_{ij}$  is the input data instance, and  $o_{ij}$  is the output of the RNN. The reconstruction error,  $\delta_i$ , can be used as the anomaly score for the given data instance.

Our Bayesian RNN is designed with one hidden layer, as depicted in Figure 2. Given the training inputs as  $X = \{x_1, \dots, x_n\}$  and their corresponding outputs as  $Y = \{y_1, \dots, y_n\}$ , we aim to find a function,  $f^w(X)$  parameterized by weights  $w$ , that is likely to generate the outputs.  $f^w(x)$  is defined as  $f^w(X) = g(W_2 h(X))$ , where  $h(X)$  is the hidden layer which is  $h(X) = g(W_1 X)$ .  $W_1$  and  $W_2$  are weights vectors defined over probability distributions; and the activation function is the rectified linear unit (ReLU) (i.e.,  $g(z) = \max(0, z)$ ).

It should be noted that Bayesian Neural Networks are based on Bayes theorem, and in general we need to find the posterior distribution of the weights. Therefore, we begin by setting a prior probability distribution on the weights,  $p(w)$ , with a Gaussian probability distribution. We, then, obtain the likelihood,  $p(Y|X, w)$ , by updating our beliefs about the prior,  $p(w)$ , after seeing the data and deciding which weights are more likely to produce the outputs. The posterior distribution  $p(w|X, Y)$  is defined over the space of the weights:

$$p(w|X, Y) = \frac{p(Y|X, w)p(w)}{p(Y|X)} \quad (2)$$



where  $p(Y|X)$  is the model evidence. However, the posterior distribution cannot be computed by Equation 2, as the model evidence is intractable for most real life problems [88], [92]. Therefore, an approximation method such as Variational Inference [93] is used to obtain an approximating distribution as:

$$q(w) = p(Y|X, w)p(w) \quad (3)$$

$q(w)$  should be as close as possible to the true posterior distribution  $p(w|X, Y)$  in Equation 2. Therefore, the Kullback–Leibler (KL) divergence<sup>3</sup> [94] of the two distributions must be minimized:

$$KL(q(w)||p(w|X, Y)) = \int q(w) \log \left( \frac{q(w)}{p(w|X, Y)} \right) dw \quad (4)$$

However, Equation 4 still contains the model evidence, so it is still intractable. This leads to the use of Evidence Lower Bound (ELBO) as an alternative to the KL divergence. The ELBO is the negative of the KL divergence up to a logarithm constant. Therefore, maximizing the ELBO is equivalent to minimizing the KL divergence which in turn lets us to approximate the true posterior distribution:

$$ELBO = \int q(w) \log p(Y|X, w) dw - KL(q(w)||p(w)) \leq \log p(Y|X) \quad (5)$$

In our Bayesian RNN, we maximize the objective in Equation 5. More details can be found in [88], [92], [95].

#### V. EXPERIMENTAL DETAILS AND RESULTS

Twenty pregnant women were recruited to participate in this study. The gestational ages of the subjects were  $12 \pm 2.1$  weeks at the beginning of the monitoring. On average, the subjects were 25.7 years old and had pre-pregnancy body mass index (BMI) of 25, with different lifestyles and background characteristics as shown in Table 1.

We excluded 7 participants from our sleep analysis, as they forgot/refused to use the wristband during sleep, with the result that their data were insufficient for our study. Therefore, in the final analysis, 13 pregnant women were included in our analysis. For these 13 subjects, we extracted valid sleep data for  $172.15 \pm 33.29$  days per person out of the total  $216.61 \pm 14.34$  days of the monitoring (79.5%). The valid sleep data included  $76.08 \pm 15.17$  days of the second trimester per person,  $78.69 \pm 12.75$  days of the third trimester, and  $17.38 \pm 10.45$  days of 1-month postpartum.

Regular phone-interviews (i.e., once or twice a month) were performed during the study to acquire subjective measurements of their status. According to the self-reports, the subjects mostly had their daily routines (i.e., regular work or study) prior to week 30, and began maternity leaves

<sup>3</sup>KL divergence, written as  $KL(p||q) = \int p(x) \log \left( \frac{p(x)}{q(x)} \right) dx$ , is a measure of the distance between probability distributions in this case  $p$  and  $q$ . A known property of the KL divergence is that is always greater or equal to zero

from weeks 30-34 through the end of our study. In addition, the participants were requested to report if they encounter sleep disturbances. On average, three women reported sleep problems at each interview till week-34, and six women experienced difficulty at sleeping in the final weeks of pregnancy. The complaints were mostly due to back pain, sickness, and visiting the toilet during nights.

In the following, we first present the eight objective sleep attributes measured from the participants during pregnancy and the postpartum; then, we demonstrate the abnormality scores calculated using our proposed approach.

#### A. SLEEP ATTRIBUTES

As discussed in Section IV-A, eight objective sleep attributes are exploited in this study to investigate the maternal sleep changes from different perspectives. To visualize the collected data, we calculate the weekly average of the sleep attributes, where each week contains valid sleep data for at least 4 days. The weeks with less than 4-days data were excluded ( $4.7 \pm 3.6$  weeks per person) to reduce the bias.

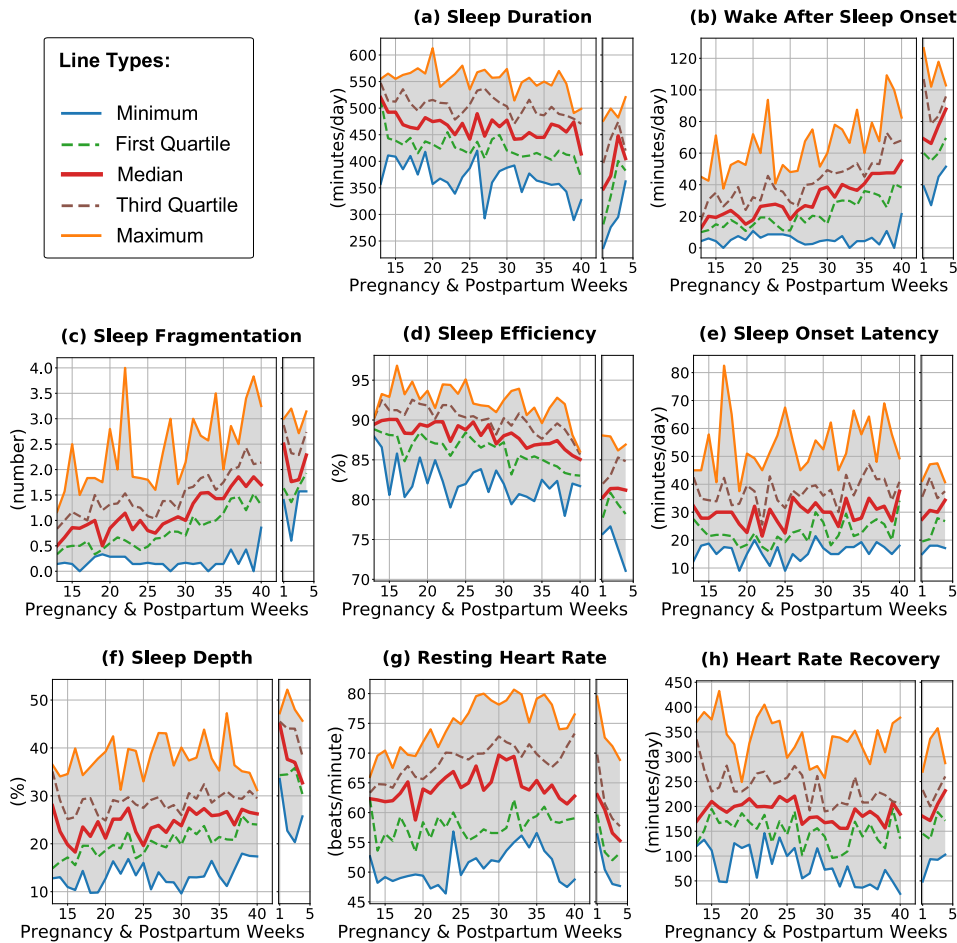
The variations in attributes for the 13 participants are illustrated in Figures 3, starting from week 13 to week 40 of pregnancy and week 1 to week 4 of postpartum. The variations are depicted by minimum, first-quartile, median, third-quartile, and maximum values of the attributes in each week. Weeks 39, 40, and 41 were the delivery weeks of 3, 7, and 3 participants, respectively. We excluded the data of week 41 in the figures, since we had the sleep data of only one participant.

*Sleep duration*, a key parameter in sleep quality assessment, gradually decreased during pregnancy. As indicated in Figure 3a, it was 8 hours and 20 minutes (median value) on the weeks 13-15, then decreased by approximately 10% and 20% in the mid and end of third trimester, respectively. It dropped to 5 hours and 50 minutes (median value) on the first week of postpartum and increased afterward.

On the other hand, the *WASO* dramatically increased (see Figure 3b). This parameter was more than 2-times higher at the third trimester and 3-times higher at the postpartum in comparison to the second trimester. Therefore, the quality of sleep diminished at the last stages of pregnancy, and it even became worse after the labor.

Similarly, *sleep fragmentation* increased, so there were more awakening times at the third trimester and postpartum as illustrated in Figure 3c. The variations of the *sleep efficiency* were in accordance with the previous attributes, where it gradually decreased throughout the pregnancy and was at the lowest after the delivery (see Figure 3d).

The increase in *sleep onset latency* was insignificant during pregnancy. As indicated in Figure 3e, the parameter slightly elevated at the third trimester (on average 30.92 minutes) in comparison to the second trimester (on average 27.69 minutes). In a similar manner, *sleep depth* hardly increased in the pregnancy (see Figure 3f). However, the parameter jumped



**FIGURE 3.** The sleep attributes of the 13 participants from week 13 to week 40 of pregnancy and week 1 to week 4 of postpartum. The variations are indicated by minimum, first-quartile, median, third-quartile, and maximum values of the attributes.

to more than 40% after the labor. Accordingly, motionless sleep (i.e., deep sleep) was relatively elevated in postpartum, although the sleep duration was less than sleep duration in the pregnancy period.

The heart-rate-related attributes are depicted in Figures 3g and 3h. *Resting heart rate* increased in the second trimester by more than 10%. However, the parameter was relatively less in postpartum, where it was, on average, 55 beats per minute at the postpartum week 4. As indicated in Figure 3h, *heart rate recovery* also changed during pregnancy. It decreased in the third trimester (on average 175.78 minutes) in comparison to the second trimester (on average 201.71 minutes).

### B. ABNORMALITY SCORE

Recall that the sleep quality score is computed through an abnormality score using our Bayesian RNN approach. The cloud server is responsible for the sleep model construction (i.e., training phase) and abnormality score calculation (i.e., testing phase). To implement the Bayesian RNN, we use the Lasagne [96] and PyMC3 [97] frameworks in Python. The input data of the method are the sleep data. Each data instance includes the eight sleep attributes of a sleep event during nighttime. The method has one input, one output, and one hidden layers, each of which has eight units (i.e., number of the sleep attributes).

1) MODEL CONSTRUCTION

As aforementioned, the training data are the “normal” data in such semi-supervised algorithms. In this study, the user’s sleep data at the beginning of the monitoring were considered as the training data. These are the data from week 13 to week 21, as the most similar data to the user’s normal condition. It should be noted that, in an ideal situation, pre-pregnancy sleep data should be selected as the training dataset (i.e., “normal” data).

The training data were normalized and fed to the model. Using the PyMC3, the weights were first initialized as normal probability distributions and then were optimized by maximizing the Evidence Lower Bound from the Equation 5. Therefore, the model was enabled to replicate the input training data at the output with the minimum error.

2) SCORE CALCULATION

The model, as a compressed representation of the training dataset, was used to reconstruct the test data. In this study, the test data were the sleep data from week 22 to the end of the monitoring. The error of a test instance reconstruction indicates the abnormality level of the test instance. Let us take two different examples. 1) The model replicates the input test data at the output with small error. This indicates the test instance is close to the training dataset (i.e., a similar sample was already seen in the training phase). Consequently, the test instance is “normal”. 2) The model reproduces the input test data at the output with large error. This shows the test instance is far from the training dataset (i.e., the instance is new to the model). Therefore, it is “abnormal”.

In this regard, the abnormality level (i.e., abnormality score) is the distance between the input and reconstructed output, calculated as:

$$s = \frac{1}{n} \sum_{j=1}^n (x_j - o_j)^2 \tag{6}$$

where  $n$  is the number of sleep attributes which is 8,  $x_j$  is the original data instance and  $o_j$  is the reconstructed data instance.

In this work, a personalized RNN model was created for each participant using her own data; and her test data were evaluated with the personalized model. The *abnormality scores* of the 13 participants are shown in Figure 4, starting from week 22. The overall median values gradually increased as the pregnancy progresses. The highest scores during pregnancy were for week 35 to the labor. At the postpartum week 1, the score jumped to more than 230% in comparison to week 40. This means that the worst sleep quality was for the first week after the labor. Afterward, the scores slightly decreased in the postpartum although they were considerably higher than the scores during the pregnancy.

VI. DISCUSSION AND EVALUATION

To the best of our knowledge, this is the first IoT-based longitudinal study that objectively assesses maternal sleep quality

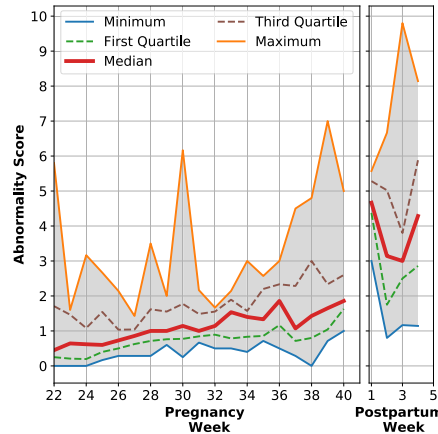


FIGURE 4. The abnormality scores of the 13 participants of pregnancy weeks 22-40 and postpartum weeks 1-4.

during pregnancy and postpartum. This IoT-based monitoring provides a feasible method to assess the quality of women’s sleep in a challenging transition period from pregnancy to motherhood. In this section, we first discuss the observations made by analyzing each attribute individually and then look into the final sleep abnormality score.

A. SLEEP ATTRIBUTES

Different objective sleep attributes indicate the quality of sleep diminished during pregnancy and in postpartum. Compared with the existing studies, this work represents a higher *confidence level* on these findings by performing *long-term* and *fine-grained quantitative* measurements and analysis of everyday data of pregnant women.

We found that the sleep duration and sleep efficiency gradually decreased across pregnancy. Correspondingly, the WASO and sleep fragmentation increased. These findings of this continuous wristband monitoring are in concordance with previous knowledge gained from short-term measurements in a few separate time points. Sleep disturbances during pregnancy could be considered unavoidable due to the hormonal, anatomical, and physiological changes in the woman’s body. For example, the levels of oxytocin, prolactin, and cortisol increase and have effects on sleep regulation. Furthermore, respiratory, musculoskeletal, and cardiovascular changes, as well as weight gain and bladder compression by the uterus have impacts on sleep [80].

Moreover, our results indicate there are more changes in these attributes after the delivery. The sleep duration and sleep efficiency drop by 21.5% and 9.7%, and the WASO and sleep fragmentation increase by 3.5 and 4.7 times, in comparison to the second trimester. These postpartum findings also comply with the previous findings; the changed life situation is a common reason for such poor sleep quality. In a previous study



by Hughes *et al.* [98], for example, the total sleep time in the first 48 hours after birth was less than 10 hours; however, breastfeeding mothers slept longer than bottle-feeding mothers. Sleep is often compromised in the postpartum period during the first months because of infants' sleep-wake patterns and various needs leading multiple night-time awakenings. Total sleep time appears to be the lowest one month after birth, but it can remain as low still at two months postpartum [39], [99]. In previous studies, these attributes were measured via subjective self-report questionnaires or short-term objective actigraphy [5], [16], [31], [100].

Based on the data in this study, the sleep onset latency did not change significantly during pregnancy; however, the difficulties of falling asleep have been reported to increase as pregnancy progresses [101]. In [101], about one-fourth of pregnant women have suffered from daytime sleepiness which might be an indicator of the insufficient sleep depth. Subjectively rated sleepiness symptoms remained the same during pregnancy [101] as did the sleep depth in this study. Interestingly, the sleep depth increased more than 40% after the delivery. This might be explained with the sleep depth accumulated during pregnancy. Findings related to the heart rate were supported by the earlier knowledge [102]; resting heart rate increased during pregnancy but decreased again during the first month postpartum, and heart rate recovery decreased toward the end of pregnancy.

### B. ABNORMALITY SCORE

Each sleep attribute represents the maternal sleep quality from a single perspective. We tackled this issue by using an abnormality score which is the fusion of the sleep attributes. It provides a better understanding of changes in maternal individual sleep quality, tailoring sleep data of early pregnancy to evaluate sleep data of late pregnancy and postpartum. In an ideal situation, changes would be evaluated against pre-conception sleep quality [103]. Moreover, it can be used to achieve personalized healthcare. The proposed score enables personalized decision-making through objective sleep quality assessment, where the intensity of the score corresponds to its distance from the user's normal condition (i.e., user's model). This personalization is important in such health-related applications, as the *normal* health condition is specific for each individual and is not easy to be generally defined. For example, average resting heart rates of two different persons could be 50 and 60 beats/min, both of which are normal values according to their individual conditions.

We evaluate the obtained abnormality scores, comparing the proposed sleep model with a baseline method. Recall that as a semi-supervised approach is used in this work, the training data are label as "normal" and the test data are unlabeled. To evaluate the model, we rely on the general hypothesis behind the model, which should produce a higher score in the case of anomalous data (i.e., differentiate "normal" and "abnormal" test instances).

In this regard, we consider a simple aggregate method as a baseline for the performance comparison. The baseline

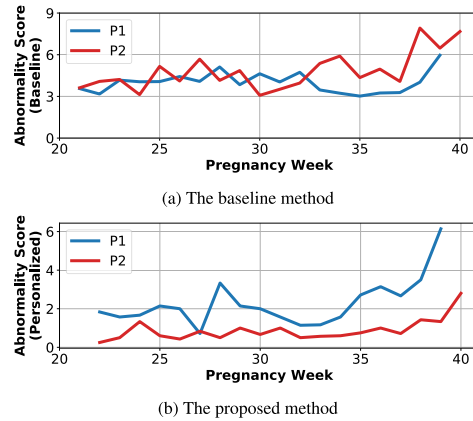


FIGURE 5. The abnormality scores of two participants, using the baseline and proposed methods.

method determines sleep quality scores using overall population values in *normal* conditions. We use the data from the beginning of the monitoring (i.e., *normal* data) representing the most probable sleep attributes of normal conditions in our study. Eventually, the baseline score of each sleep event is the sum of distances between the sleep attributes and their corresponding normal population means in units of the standard deviations.

We select two participants (i.e., P1 and P2) with different conditions to implement the comparison between the proposed method and the baseline. P1 experienced substantial changes in her sleep although P2 had relatively less sleep changes in pregnancy. Table 2 shows average values of some sleep attributes of P1 and P2 in their normal conditions (i.e., beginning of the monitoring) and at the end of the pregnancy. The table also indicates attributes changes (ratio), comparing data at the end of pregnancy to population data and to her own data. As indicated, the ratio of P1 attributes to her own data is higher than the ratio to the population data. On the other hand, the ratio of P2 attributes to her own data is relatively less.

As shown in Figure 5a, the baseline score is unable to accurately distinguish between P1 and P2. This is because P1's sleep parameters, despite the substantial changes, were close to the population values. In contrast to the baseline method, the sleep changes are clearly visible using the abnormality score obtained from the proposed model (see Figure 5b). This enables the provision of tailored individualized and effective care, where we can identify those who need the care most and optimize resource allocation.

### C. LIMITATIONS AND FUTURE DIRECTIONS

The proposed IoT-based system is a proof-of-concept for 1) long-term monitoring of maternal daily sleep 2) effective care for maternal sleep disturbances using personalized

**TABLE 2.** P1 and P2 attributes and the ratio of the attributes at the end of pregnancy to her own data and population values.

Attributes	#	Mid of second trimester	End of third trimester	Ratio to popul. data	Ratio to her own data
Sleep fragmentation (times)	P1	0.5	1.53	1.62	3.06
	P2	1.39	2.29	2.43	1.64
WASO (minutes)	P1	15.3	37.32	1.48	2.43
	P2	34.39	75.83	3.02	2.2
Sleep duration (minutes)	P1	389.34	341.25	0.71	0.87
	P2	480.04	456.33	0.95	0.95
Resting heart rate (beats/min)	P1	53.38	59.23	0.96	1.2
	P2	65.61	71.17	1.16	1.08

decision-making. One of the limitations of this study is that the study sample is small. Other studies investigate the associations between subjective sleep measurements and other pregnancy-related parameters and complications on large study samples. For example, Okun *et al.* [104] conduct a study on 166 pregnant women via self-report questionnaires and indicate that poor sleep quality is correlated with an increased risk of preterm birth. Another study is performed on 457 pregnant women to tackle the association between sleep quality and type of delivery and length of the labor [22]. Unfortunately, we are unable to statistically investigate such associations in our data since our sample size is smaller. Future directions of this study are to perform objective longitudinal studies on a larger population focusing on such correlations.

Another limitation of our monitoring study is linked to the data collection. We were bounded to one wristband that monitored heart rate, step counts, and body movements. Future work will consider multimodal and multisensor data collection and integration with more advanced sensor nodes, enabling the capture of additional health/sleep attributes. For instance, PPG as a non-invasive and convenient technique can play a significant role in such monitoring systems [69]. Finger-based and wrist-based PPG sensors can be leveraged in this regard to continuously acquire different health parameters such as heart rate variability and respiration rate. Moreover, strap monitors can be employed to record EMG signals for possible abdominal contractions extraction. However, to enhance the feasibility of long-term monitoring, there needs to be a balance between the number of wearables and their continuous use, as a high number of wearable devices could be impractical or inapplicable for sustained long-term monitoring. For instance, in our study, despite using only one wristband for the data collection, we were required to exclude the sleep data of 7 participants out of 20 due to the high volume of missing data. The main reasons were forgetfulness and refusal of wearing the wristband during sleep.

Finally, it is worth noting that the proposed model can be extended to *contextual anomalies* methods, considering the contextual information. These longitudinal studies demand remote and in-home monitoring in which the participants might be involved in different conditions and environments.

Therefore, context information including personal lifelogging data, ambient data, and medication reports can improve the accuracy of the personalized decision-making.

## VII. CONCLUSION

Maternal sleep quality alters during the pregnancy and postpartum due to the adaptations of the maternal body. Such variations in sleep should be closely monitored as poor sleep quality might lead to various pregnancy complications. Conventional studies are insufficient for this issue as they are limited to restricted data collection approaches. In this paper, we conducted an objective longitudinal study to thoroughly investigate maternal sleep adaptations in pregnancy and postpartum. We introduced an IoT-based system to remotely monitor pregnant women 24/7. Several sleep attributes were extracted to observe changes in maternal sleep patterns. Moreover, we proposed a Bayesian RNN approach to construct a personalized sleep model for each individual using her own data. The sleep model was utilized to deliver an abnormality score, which indicated the degree of maternal sleep quality adaptations. In total, we collected 7 months of data from 20 pregnant women; however, we only included  $172.15 \pm 33.29$  days of valid sleep data per person from 13 pregnant women in our sleep analysis. For each subject, the sleep model was created using the data from the beginning of the monitoring, and the model was tested on the rest of the pregnancy and postpartum data. The obtained scores showed that sleep abnormalities increased during the pregnancy (2.87 times) and after the delivery (5.62 times) in comparison to the mid of the second trimester. This work indicated sleep quality decreased in pregnancy and postpartum with a high confidence level, leveraging fine-grained quantitative measurements and analysis on everyday data of pregnant women.

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