Bringing Intelligence to the Edge: Towards Smart and Adaptive Residential Learning Healthcare Systems

Doctoral Thesis

Biomedical Engineering

School of Biological Sciences

Author:

Nada Fares

Supervisor:

Eur Ing Professor R. Simon SHERRATT

30 October 2023

Declaration of Authorship

I confirm that this thesis titled: “Bringing Intelligence to the Edge: Towards Smart and Adaptive Residential Learning Healthcare Systems” is my own work and the use of all material from other sources has been properly and fully acknowledged.

Abstract

In light of an increasingly aging population, it becomes crucial to preserve good health and independence for as extended a period as feasible. Rather than hospitalization and placement in institutional care, individuals facing chronic illnesses or physical limitations can benefit from the support of smart healthcare Information and Communication Technology (ICT) solutions, right in the comfort of their own homes.

Currently, there is a shift in healthcare ICT solutions towards more balanced approaches that integrate hospitals and homes, with the ultimate goal of transitioning to home-centric healthcare systems in the future. However, for this evolution to progress, it necessitates the integration of new technologies, system architectures, and computing paradigms.

As this transformation advances towards the concept of Learning Healthcare Systems (LHS) it brings forth fresh challenges that must be addressed to meet evolving requirements. To enable the development of home-centric healthcare solutions it is essential to extend the concept of LHS to personal residences by incorporating intelligent Edge computing.

A gateway is a key component in residential healthcare systems. By enhancing its adaptability and imbuing it with intelligence, we can elevate residential healthcare systems to the status of Learning Healthcare Systems (LHSs), capable of making real-time decisions. To develop adaptable consumer gateways for consumer healthcare applications, this research work outlines a set of technical requirements concerning scalability, reliability, availability, interoperability, energy efficiency, and privacy that need to be fulfilled before any product or service can be created.

This research work aims to provide the requirements for the innovation of a one-for-all smart adaptive consumer gateway in residential learning healthcare systems and to influence the consumer healthcare field to consider the benefits of moving to adaptive gateways for future developments.

Acknowledgments

Attaining a Ph.D. degree is an emotional journey that begins with excitement, transitions into periods of isolation and despair, and ultimately culminates in joy and triumph. This lengthy journey is never a solitary endeavor; instead, it encompasses the contributions of certain individuals, to whom I extend my heartfelt gratitude.

First of all, I wish to express my gratitude to my advisor, Professor R. Simon Sherratt, for all the encouragement, support, guidance, and endless motivation throughout the journey of my Ph.D. I truly appreciate his efforts and advice that were essential for the completion of this Doctoral Thesis.

My special thanks go to my husband, Husam Fares, who has been my unwavering support from the very beginning, serving as the solid foundation I relied on during all the challenging times. I am grateful for your patience and belief in me.

Additionally, I'd like to express my gratitude to my children, Yasmin, Yousef, Camillia, and Linnea, for their love, understanding, and emotional support. It was their support and encouragement that made this dissertation achievable.

Finally, I wish to extend my appreciation to my parents for their constant support, and of course, to God for blessing me with the courage, determination, and strength required to successfully complete this journey.

Table of Content

List of Figures

List of Tables

List of Code Boxes

List of Text Boxes

Chapter 1. Introduction

1.1 Motivation

The Internet of Things (IoT) represents a modern communication paradigm that envisions a future where everyday objects are equipped with microcontrollers, digital communication transceivers, and suitable protocol stacks. These enhancements enable these objects to seamlessly communicate with each other and users, seamlessly integrating into the Internet [1]. IoT seeks to make the Internet more immersive and all-encompassing by facilitating effortless access and interaction between an extensive range of devices, including home appliances, surveillance cameras, monitoring sensors, actuators, displays, and more. These interactions enable the exchange of information between objects regarding their characteristics, such as operational status, temperature, motion, location, and more. The ultimate goal is to facilitate instant data analysis and intelligent decision-making and action. This paradigm enables the development of practical applications across a multitude of domains, including home automation, medical assistance, mobile healthcare, support for the older individuals, and many others [2].

The world's population is aging, and there is an increasing need for solutions to support the health, well-being, and independence of older individuals. The majority of older individuals opt to remain in their familiar homes as they age, and various technologies such as the Internet of Things (IoT), technologies for Ambient/Active Assisted Living (AAL), and artificial intelligence (AI) can facilitate and enhance their ability to live independently [3]. Research in this area directly addresses a pressing societal challenge. IoT and AI technologies can empower older adults to live longer and independently by developing innovative solutions that can directly impact society by improving the lives of older adults, reducing healthcare costs, and addressing critical challenges related to aging [4]. The intersection of IoT and AI is still a fertile ground for innovation, thus performing research on how to direct and orient IoT and AI solutions to address the individual needs of the older adults living in their own environment could lead to groundbreaking solutions that are patient/consumer oriented. IoT and AI can be harnessed to monitor health conditions, provide timely interventions, and enable better management of chronic illnesses. This research can lead to healthcare systems that are more responsive and tailored to the unique needs of older adults.

IoT (Internet of Things) and AI (Artificial Intelligence) technologies can significantly enhance the development of residential healthcare systems by providing real-time data collection, analysis, and intelligent decision-making capabilities. IoT devices can continuously monitor a patient's vital signs, activity levels, and other health-related data [5]. AI algorithms can analyze this data in real-time, detecting abnormalities and trends that may require attention. This continuous monitoring helps in early detection of health issues and can trigger timely interventions. In addition, AI can analyze a patient's historical health data and IoT-generated real-time data to create highly personalized care plans. These plans can include tailored medication schedules, dietary recommendations, and exercise routines, considering the individual's unique health needs and preferences. AI can leverage historical patient data to make predictions about future health outcomes. IoT-enabled devices allow healthcare providers to remotely monitor patients' health conditions. AI can analyze the data from these devices and provide real-time alerts if any critical parameters deviate from the norm. This enables early intervention and reduces the need for frequent in-person visits to healthcare facilities. IoT-connected medication dispensers can remind patients to take their medications on time. AI algorithms can track medication adherence and send alerts to patients or caregivers if doses are missed. This promotes medication compliance, particularly for patients with chronic conditions. IoT-generated health data can be seamlessly integrated with Electronic Health Records (EHRs) through AI-driven systems [6]. This ensures that healthcare providers have a complete and up-to-date view of a patient's medical history, enabling better-informed decision-making. IoT devices can monitor a patient's daily activities and behaviors. AI can analyze this data to provide insights into lifestyle factors that may impact health, such as sleep patterns, exercise routines, and dietary habits. Patients can receive personalized feedback and recommendations for making healthier choices. AI systems in residential healthcare can learn and adapt over time [7]. They can refine care plans based on new data, patient responses, and outcomes. This adaptive learning helps in continually improving the effectiveness of healthcare interventions. IoT and AI can help reduce healthcare costs by preventing hospital readmissions, complications, and emergency room visits. Early detection and intervention can lead to better health outcomes and lower healthcare expenses [8].

The motivation behind developing Residential Learning healthcare systems that are patient/consumer oriented has driven the current research to search for and identify all the building blocks of this system, the healthcare data sources, the residential components, and the remote components. The research Identify the best practices performed in each block and the level of their technological readiness and comes up with a set of requirements that covers different aspects of designing and implementing such solutions.

1.2 Holistic Objective

“Identify the technical requirements for the innovation of a one-for-all smart adaptive patient/consumer-oriented residential learning healthcare system and design its architecture to influence the patient/consumer healthcare field to consider the benefits of moving from fixed to adaptive gateways.”

This research is set out to introduce a holistic residential healthcare solution that performs a set of tasks to assure the good health, wellbeing, and safety of the patients/consumers living in their own environment. While there has been many research and development in healthcare monitoring systems for the aging population, it is declared that most of the developed healthcare monitoring systems to date scarcely focused on being consumer-oriented, affordable, or managed the patient's health condition rather than characterized it [9] [10]. In an attempt to fulfill the identified gaps of the available healthcare monitoring solutions, this research is directed to deliver a holistic approach that targets the individual needs of patients/consumers.

To be able to develop the introduced adaptive residential learning healthcare system, we need to identify a set of requirements concerning scalability, energy efficiency, reliability, availability, interoperability, and privacy that needs to be fulfilled before any product or service can be created. Intervention in local data processing, local data storage, embedded data mining, security, interoperability, and configurability that could serve the development process need to be addressed.

1.3 Aims and Objectives

The main aim of this research is to attain or maintain the highest practicable physical, mental, and psychosocial well-being of older adults. Thus, the proposed solution must ensure that older adults health improve when possible and do not deteriorate unless the older individual's clinical condition demonstrates that the decline was unavoidable.

To achieve this goal an assessment and prevention healthcare solution is required to design and implement individualized care plans and practices for elderly patients living in their own environment. The primary purpose of this system is to identify patient's care problems and address them in an individualized healthcare solution that adapts to the patient's/consumer healthcare changing requirements and can perform local decision making in real time to avoid any unexpected health deterioration.

A set of objectives were set to achieve the aim of this research:

- ✓ Investigate the factors that affect the quality of life of the aging population.
- ✓ Explore the chronic diseases and comorbidities that encounter the aging population and the effect they have on the aging individual’s quality of life.
- ✓ Analyze the state of the art of ICT solutions for older people with chronic conditions, and the impact of these solutions on their quality of life from a biomedical perspective.
- ✓ Identify the limitations in the up-to-date healthcare ICT solutions.
- ✓ Propose a set of technical requirements for the development of residential learning healthcare solution that adapts to the needs of individual patients/consumers.
- ✓ Design the architecture of the proposed residential learning healthcare system.
- ✓ Conduct a proof-of-concept demonstration of a residential LHS with an adaptive gateway architecture based on machine learning.

1.4 Research Design, Method, and Scope

The present research takes a multidisciplinary approach by tapping into biomedical engineering, computer engineering, public health, and physiology. Acquiring new knowledge in multiple disciplines and merging the attained knowledge to serve the aim of the research was a big challenge. Thus, the research design is divided into stages based on the list of objectives identified earlier in this chapter.

Each stage requires intensive literature review that provides significant outcomes that play a role in directing the research in the following stages. The surveillance of the ageing population and the role of chronic diseases in affecting their quality of life, is reviewed, and analyzed in chapter 2. This chapter acts as the outstanding pillar on which the other stages of this research rely.

This process carries with it a risk of misleading the research in the wrong direction. Thus, at different stages of the research we published the attained outcomes in peer-reviewed academic journals to make sure the research is on the right track. The first publication, presented in chapter 3, addresses a literature review of the state of the art of IoT healthcare solutions for the aging population and acted as a feasibility study that plays a role in confirming the direction and validated the concept of the current research. Then, Investigating the state of the art of IoT healthcare solutions for the aging population helps in identifying the challenges and limitations of these solutions. This outcome oriented the research to innovate a list of requirements for the development of residential learning healthcare systems that addresses the limitations and challenges of previously developed systems. The second publication, addressed in chapters 4, 5, and 6, provides the methodology, technical requirements, design, and a proof-of-concept of the proposed residential learning healthcare system. Publishing this paper in a consumer-oriented academic journal determined that the proposed research offers a novel and timely perspective on the future of consumer healthcare.

The delivery of a technical set of requirements, discussed in chapter 5, serves the holistic approach of covering all aspects of developing a consumer-oriented residential learning healthcare system. This stage is performed through a deep literature review followed by an integrated analysis that led to an identification of the required components of the proposed system, and the required characteristics for each component to achieve the holistic image of the system. But to prove the validity of the proposed requirements and to provide an architectural design of the proposed system an experiment is performed and discussed in chapter 6. However, the performed experiment didn’t cover all the proposed requirements. Thus, a group of requirements as local data storage, system integration with remote data sources, creation of a user interface, and the integration with remote cloud services for advanced analysis and decision making where out of the scope of the experiment performed.

1.5 Research Output

This research has yielded two papers that have been successfully published in highly respected journals. This accomplishment signifies a significant milestone and underscores the importance of the findings of this research in the wider scientific community.

The first paper is a systematic review of ICT Healthcare Solutions with the title: "Directing and Orienting ICT Healthcare Solutions to Address the Needs of the Aging Population". This paper is published in MDPI Healthcare Journal with the Doi link: https://doi.org/10.3390/healthcare9020147.

The second paper is a position paper identifying the technical requirements for adaptive consumer-oriented gateways in residential LHSs and provides a design of the architecture of the proposed residential LHS. This paper has the title: "Requirements for Adaptive Consumer Gateways in Residential Learning Healthcare Systems: Bringing Intelligence to the Edge". This paper is published in IEEE Transactions for Consumer Electronics Journal with the Doi link: https://doi.org/10.1109/TCE.2023.3326570.

1.6 Research Organization

The presented research is organized as follows. *Chapter 2* provides a literature review on the surveillance of the aging population from a public health perspective. This chapter presents a physiological perspective of how the aging population is affected by chronic diseases and comes up with the aspects to be monitored and assessed to attain better quality of life of the aging population living in their own environment. *Chapter 3* presents a copy of a published systematic literature review on directing and orienting ICT healthcare solutions to address the needs of the aging population. *Chapter 4* describes the methodology for the development of residential learning healthcare systems with Edge Computing. This chapter defines Learning healthcare systems and shows how they can serve as an extension to the available ICT healthcare solutions. A presentation of the different phases and components of the proposed residential learning healthcare system is provided. *Chapter 5* presents the proposed Requirements for Consumer-oriented Residential Learning Healthcare Systems. The proposed architecture of the residential learning healthcare system, and the experimental work performed is discussed in *Chapter 6*. *Chapter 7* communicates all the findings from previously stated research objectives, and further discusses the results and observations related to the research. Finally, Chapter 8 summarizes research conclusions and future work.

References

[1] L. Atzori, A. Iera, and G. Morabito, "The internet of things: A survey," Comput. Netw., vol. 54, no. 15, pp. 2787–2805, 2010.

[2] A. Zanella, N. Bui, A. Castellani, L. Vangelista, and M. Zorzi, "Internet of Things for Smart Cities," IEEE Internet of Things Journal, vol. 1, no. 1, pp. 22-32, Feb. 2014. DOI: 10.1109/JIOT.2014.2306328.

[3] R. Shah and A. Chircu, "IoT and AI in healthcare: A systematic literature review," Issues in Information Systems, vol. 19, no. 3, 2018.

[4] S. Majumder, E. Aghayi, M. Noferesti, H. Memarzadeh-Tehran, T. Mondal, Z. Pang, and M. J. Deen, "Smart Homes for Elderly Healthcare—Recent Advances and Research Challenges," Sensors, vol. 17, no. 11, pp. 2496, 2017. DOI: 10.3390/s17112496.

[5] A. Haleem, M. Javaid, and I. H. Khan, "Current status and applications of Artificial Intelligence (AI) in medical field: An overview," Current Medicine Research and Practice, vol. 9, no. 6, pp. 231-237, 2019.

[6] C. Dinh-Le, R. Chuang, S. Chokshi, and D. Mann, "Wearable health technology and electronic health record integration: scoping review and future directions," JMIR mHealth and uHealth, vol. 7, no. 9, pp. e12861, 2019.

[7] A. Budrionis and J. G. Bellika, "The learning healthcare system: where are we now? A systematic review," Journal of biomedical informatics, vol. 64, pp. 87-92, 2016.

[8] B. Mohanta, P. Das, and S. Patnaik, "Healthcare 5.0: A paradigm shift in digital healthcare system using artificial intelligence, IOT and 5G communication," in 2019 International Conference on Applied Machine Learning (ICAML), pp. 191-196, IEEE, May 2019.

[9] P. M. et al., "Health–Related ICT Solutions of Smart Environments for Elderly–Systematic Review," IEEE Access, vol. 8, pp. 54574-54600, 2020.

[10] E. S. L. Liu, I. Nikolaidis, A. Miguel-Cruz, and A. R. Rincon, "Smart homes and home health monitoring technologies for older adults: A systematic review," International Journal of Medical Informatics, vol. 91, pp. 44-59, 2016.

Chapter 2. Aging and Gerontechnology

Literature Review

2.1 Aging and Health Decline

Aging is a natural, progressive, and heterogeneous process for all human beings. The aging process is characterized by different aspects (morphological, pathophysiological, psychological, social, and environmental) that are commonly explored in "gerontology". In each aspect, age is measured by the functional abilities of the person. Therefore, the health status of an older person is the result of the additive effects of aging as well as the attained diseases. This situation leads the older person to a state of "unstable incapacity" for "normal aging" [1]. Aging is characterized by a reduced reaction to the environment and to certain pathologies with obvious decrease of autonomy and integration in Activities of Daily Living (ADL). It has major effects on most of the body systems such as nervous, metabolic, sensory, cardiovascular, respiratory, and musculoskeletal. These effects are more observable in the musculoskeletal system in terms of locomotion and mobility [2]. This concludes that aging of the population and the onset of chronic diseases are interconnected. The result of the aging process is a general physical and functional weakening which will eventually increase the risk of fall incidents. Falls are considered among the most hazardous incidents that can strike an elderly person. Each year approximately 28-35% of people aged 65 and over fall worldwide increasing to 32-42% for those over 70 years of age [3]. Based on the latest Falls Fact Sheet published by the World Health Organization, Falls are the second leading cause of accidental or unintentional injury deaths worldwide. Each year an estimated 646 000 individuals die from falls globally of which over 80% are in low- and middle-income countries. Adults older than 65 years of age suffer the greatest number of fatal falls. 37.3 million falls that are severe enough to require medical attention occur each year [4]. Despite their unavoidable risk, falls could be managed, detected, and even prevented if proper means are administered to the older person. These incidents require both human and technical interventions. This dual support is accounted for “gerontechnology”. The outcome of this discipline shall be measured in terms of gain of independence and improved quality of life [5].

Most falls and resulting injuries among older persons are shown to result from a combination of age and chronic disease-related conditions and the individual’s interaction with their social and physical environment [6]. It is also known that risk is greatly increased for those with multiple risk factors [7]. This is good evidence to show the need for healthcare monitoring ICT solutions for older adults that require healthcare monitoring on a daily basis.

It is estimated that by the year 2050 one or more in each group of five people will be aged 65 years or above. This demographic change will induce a high rate of fall related injuries in the aging population [3]. Cognitive decline occurs as a natural part of the ageing process and can impact on functional ability and therefore, lead to increased risk of falls and near falls [8]. Thus, this increasing weight of demographic change leaves new challenges on socio-economic levels if appropriate measures are not taken to tolerate the impact of this inevitable ageing and its associated fallouts.

2.2 Aging in Low- and Middle-Income Countries - Lebanon

Lebanon is a country in transition with limited resources. Lebanon is currently experiencing unique and dynamic demographic shifts towards an aging population. People aged 65 years and above currently represent 7.3 percent of Lebanon's population and this percentage is projected to increase to 12.0 percent and 21.0 percent by the year 2030 and 2050, respectively [9]. Decreased fertility and success against child mortality and infectious diseases, plus the "return migration" of older Lebanese workers from neighboring hosting countries have resulted in the increase in the number and proportion of the older population [10].

The aging of the population greatly challenges health care systems in countries with limited resources. A study in the Western Asia Region (Middle East region) found that 40% of older people aged 65 and above fell each year in Lebanon [11]. As the older population in Lebanon grows and ages, a proper healthcare system will become more and more necessary to ensure the health of the entire aging population. To date, the healthcare implications of rapid aging in Lebanon have not been adequately acknowledged by healthcare providers and remain relatively under-researched. Thus, a comprehensive healthcare plan for the aging population needs to be designed and implemented into the healthcare system with the least resources first. Such changes can affect the health system at several levels and start a chain reaction for further change in the future.

The demographic transition in Lebanon is accompanied by an epidemiological transition, with noncommunicable and degenerative diseases (NCD) [10]. The national Pan Arab Project for Family Health (PAPFAM) survey, conducted by the Central Administration of Statistics and the Ministry of Social Affairs in 2004, reveals that around three quarters of older persons in Lebanon report at least one co-morbid condition and one quarter perceive their health status as poor. Hypertension (36.7 percent), heart disease (23.1 percent) and diabetes (21.5 percent) constitute the leading causes of morbidity [12]. Given the situation, healthcare delivery pathways need to be methodized, keeping in mind the prevalence of chronic diseases, comorbidities, and polypharmacy requirements of the older people.

Chronic diseases such as atherosclerosis, osteoporosis, cardiovascular diseases, obesity, diabetes, dementia, and osteoarthritis require quick diagnosis and continuous supervision by a professional caregiver. This is concurrent with the fact that there is a ratio of 1 geriatrician for every 465 older adults and 1 nurse with specialization in gerontology for every 523 older adults in nursing homes in Lebanon as stated in the National Report on Services Available to Older People in Lebanon, 2010 [12].

2.3 Chronic Diseases and Their Impact on Aging

Chronic diseases are long-term health conditions that persist over time and often worsen with age. In the aging population, there is an increased prevalence of chronic diseases due to factors such as physiological changes, lifestyle choices, and genetic predisposition. Common chronic diseases in the aging population include *cardiovascular diseases* (such as hypertension and heart disease), respiratory diseases (such as chronic obstructive pulmonary disease), *diabetes, arthritis, and neurodegenerative disorders* (such as Alzheimer's disease). It has been estimated that between 55% and 98% of older adults aged 60 years and over have at least 2 chronic diseases (comorbidity) where cardiovascular diseases are the most common conditions in comorbid patients [13]. These conditions can significantly impact the quality of life and require ongoing management and care. It is important for healthcare systems to address the specific needs of the aging population and provide appropriate support and interventions to manage chronic diseases effectively.

2.3.1 Cardiovascular Disease (CVD)

Cardiovascular diseases refer to long-term conditions that affect the heart and blood vessels. These conditions include hypertension (high blood pressure), coronary artery disease, heart failure, and arrhythmias. Cardiovascular disease has a significant impact on the aging population. It is estimated that 70% of people over 70 years old will develop CVD and that more than two thirds will also have associated non cardiovascular comorbidities [13]. As individuals grow older, the risk of developing CVD increases, and its consequences can be particularly severe. Factors such as the accumulation of plaque in arteries (atherosclerosis), high blood pressure (hypertension), and changes in the heart's structure and function all contribute to this increased risk [14].

Cardiovascular disease remains one of the leading causes of death among older adults worldwide. Conditions like heart attacks and strokes are often the result of underlying CVD. CVD can have a significant impact on an aging individual's quality of life. It can lead to symptoms such as chest pain (angina), shortness of breath, and fatigue, which can limit physical activity and overall well-being. Aging individuals with CVD are at higher risk for complications, including heart failure, arrhythmias (irregular heartbeats), and peripheral artery disease (narrowing of arteries in the limbs). These conditions can further reduce mobility and independence. Many older adults have multiple chronic health conditions, and CVD often coexists with other conditions such as diabetes, obesity, and chronic kidney disease. Managing these comorbidities can be complex and may require multiple medications and lifestyle changes [13].

Cardiovascular disease imposes a significant economic burden on the aging population in terms of healthcare costs. Treating and managing CVD-related conditions, including hospitalizations, medications, and surgeries, can be expensive. Aging individuals can take steps to reduce their risk of CVD by adopting healthier lifestyles. This includes maintaining a balanced diet, engaging in regular physical activity, managing stress, and avoiding smoking and excessive alcohol consumption. In some cases, medications like statins, blood pressure medications, and blood thinners may be prescribed to manage CVD risk factors. Interventional procedures such as angioplasty and stent placement or even surgery may be necessary to treat advanced CVD. Regular check-ups and screenings are important for early detection and prevention of cardiovascular disease in the aging population. These screenings can help identify risk factors and allow for timely interventions. In cases where CVD has progressed significantly, palliative care may be necessary to improve the quality of life for older adults with CVD. This approach focuses on symptom management, pain relief, and emotional support.

Dealing with a chronic condition like cardiovascular disease can lead to anxiety, depression, and decreased overall mental well-being, affecting an individual's quality of life. It can result in reduced independence, as older adults may require assistance with daily tasks and may no longer be able to live independently. Individuals with CVD may become socially isolated due to their condition. They may avoid social activities or gatherings due to their symptoms or limitations, leading to a decreased quality of life.

In conclusion, cardiovascular disease has a profound impact on the aging population, affecting both longevity and quality of life. Preventive measures, early detection, and effective management strategies are essential to reduce the burden of CVD on older adults and improve their overall health outcomes.

Managing strategies could be achieved by properly managing medications and adhering to treatment plans that help control CVD risk factors and reduce the likelihood of complications. Providing support and education to older adults and their caregivers can help them better understand CVD, manage their condition, and improve their overall quality of life. Finally, monitoring cardiovascular chronic diseases is crucial for managing and preventing complications. Some key aspects to monitor are [15]:

- ✓ *Blood Pressure:* Regular monitoring of blood pressure is essential to manage hypertension. It helps determine if blood pressure is within a healthy range or if medication adjustments are needed.
- ✓ *Cholesterol Levels:* Monitoring cholesterol levels, including LDL (bad) cholesterol and HDL (good) cholesterol, helps assess the risk of developing or worsening cardiovascular disease. It may involve periodic blood tests.

- ✓ *Blood Sugar Levels:* For individuals with diabetes or prediabetes, monitoring blood sugar levels is important to prevent complications that can impact cardiovascular health.
- ✓ Heart Rate and Rhythm: Monitoring heart rate and rhythm can help detect irregularities or abnormalities, such as arrhythmias. This can be done through regular check-ups or by using wearable devices like heart rate monitors or smartwatches.
- ✓ Weight and Body Mass Index (BMI): Maintaining a healthy weight and BMI is crucial for cardiovascular health. Regular monitoring of weight and BMI can help identify any significant changes that may require intervention.
- ✓ Lifestyle Factors: Monitoring lifestyle factors such as diet, physical activity, smoking, and alcohol consumption is important. Making healthy choices in these areas can significantly reduce the risk of cardiovascular disease.
- ✓ Health conditions: Monitoring other health conditions to keep record of comorbidities as well as inspecting the effect of factors such as psychological well-being, nutrition, pain, and medications on the quality of life of the aging person with CVD.

It is important to work closely with healthcare professionals who can provide guidance on monitoring these aspects and develop an individualized care plan for managing cardiovascular chronic diseases with the help of ICT solution.

2.3.2 Respiratory System Diseases

Respiratory System diseases are long-term conditions that affect the lungs and airways. Common examples include chronic obstructive pulmonary disease (COPD), asthma, bronchiectasis, and interstitial lung diseases. COPD is a highly prevalent condition that is expected to be the third cause of death worldwide in the aging population [16].

COPD is a chronic lung disease that progressively worsens over time. It encompasses several conditions, primarily chronic bronchitis, and emphysema, characterized by airflow obstruction and difficulty breathing. COPD can have a significant impact on the aging population in several ways. The risk of developing COPD increases with age, and it is most commonly diagnosed in individuals over the age of 40. Long-term exposure to risk factors such as smoking and environmental pollutants contributes to the development of COPD. COPD leads to a gradual decline in lung function. As individuals age, their lung function naturally decreases, and COPD exacerbates this decline, resulting in greater difficulty breathing and reduced physical capacity [16].

COPD symptoms, which include chronic cough, excessive mucus production, shortness of breath, and chest tightness, can severely impact an individual's quality of life. These symptoms can limit mobility and the ability to engage in daily activities. COPD exacerbations, which are acute worsening of symptoms, become more common as individuals age. These exacerbations often lead to hospitalizations and can be life-threatening [17].

Older adults with COPD are at a higher risk of developing other health conditions such as cardiovascular disease, osteoporosis, and depression. Managing multiple chronic conditions can be challenging and further impact overall health. These comorbid conditions have consequences for the clinical presentation and prognosis of patients with COPD. Hence, their identification and treatment are key elements in COPD management [17].

COPD can lead to functional impairment, making it difficult for older adults to perform essential activities of daily living, such as bathing, dressing, and cooking. This can result in a loss of independence. COPD can lead to social isolation and emotional distress. As the disease progresses, individuals may withdraw from social activities due to embarrassment about their symptoms or limitations in physical function. Older adults with COPD often require frequent medical care, including doctor visits, medications, and pulmonary rehabilitation. This can place a significant burden on healthcare resources and contribute to rising healthcare costs.

In summary, COPD is a chronic lung disease that has a substantial impact on the aging population. It can result in decreased lung function, impaired quality of life, and increased healthcare utilization. Effective management and preventive measures are essential to reduce the burden of COPD on older adults and enhance their overall well-being.

Monitoring respiratory system chronic diseases as COPD is crucial for managing symptoms, preventing exacerbations, optimizing lung function, and maintenance of the best possible quality of life. Some key aspects to monitor are:

- ✓ *Lung Function Tests*: Spirometry is a common lung function test that measures how much air you can inhale and exhale and how quickly you can do so. It helps assess the severity of respiratory diseases and monitor changes over time.
- ✓ *Oxygen Levels*: Monitoring oxygen saturation levels using a pulse oximeter can help determine if the lungs are efficiently oxygenating the blood. Low oxygen levels may indicate the need for supplemental oxygen therapy.
- ✓ Peak Expiratory Flow (PEF): PEF monitoring is commonly used for individuals with asthma. It measures the maximum speed at which a person can exhale air and helps assess the degree of airway obstruction.
- ✓ Symptoms and Quality of Life: Regularly monitoring symptoms such as cough, shortness of breath, wheezing, and chest tightness is important. Assessing the impact of these symptoms on daily activities and quality of life can guide treatment decisions.
- ✓ Medication Usage: Monitoring the use of respiratory medications, such as inhalers or nebulizers, helps ensure adherence to prescribed treatments and identify any changes in medication needs.
- ✓ Environmental Triggers: Identifying and monitoring exposure to environmental triggers, such as allergens or pollutants, can help manage respiratory symptoms and prevent exacerbations.
- ✓ Vaccination Status: Monitoring vaccination status, particularly for respiratory infections like influenza and pneumonia, is important for individuals with

respiratory system chronic diseases. Vaccinations can help prevent complications and reduce the risk of respiratory infections.

- ✓ Physical Activity Assessment: Encourage physical activity and assess the older adult's ability to engage in exercise. Physical activity can improve lung function and overall health.
- ✓ Nutrition Assessment: Assess the older adult's nutritional status. A balanced diet is important for maintaining strength and overall health. Malnutrition can exacerbate COPD symptoms.
- ✓ Smoking Cessation Support: Ensure that older adults with COPD are not smoking and provide support for smoking cessation if needed. Smoking cessation is one of the most effective ways to slow the progression of COPD.
- ✓ Exacerbation Action Plan: Develop an exacerbation action plan in collaboration with the healthcare provider. This plan should outline steps to take when symptoms worsen, including when to seek medical attention or adjust medication.
- ✓ Mental Health Assessment: Assess the older adult's mental health, as COPD can lead to anxiety and depression. Offer support and referral to mental health services if needed.
- ✓ Education: Provide education to both the older adult and their caregivers about COPD management, including the importance of medication adherence, symptom recognition, and lifestyle modifications.

Regular and comprehensive monitoring, along with appropriate interventions, can help older adults with COPD manage their condition effectively and maintain the best possible quality of life. It is essential to tailor the monitoring plan to the individual's specific needs and the severity of their COPD. It is crucial to work closely with healthcare professionals, such as pulmonologists or respiratory therapists, who can provide guidance on monitoring these aspects and develop an individualized management plan for respiratory system chronic diseases with the support of ICT solutions to provide the aging population with a better quality of life.

2.3.3 Diabetes

Diabetes is a chronic disease that affects the body's ability to regulate blood sugar levels. In the aging population, the prevalence of diabetes increases, and managing the condition becomes crucial. More than 25% of adults >65 years of age have diabetes [18]. Both aging and diabetes increase the risk of certain comorbidities including cognitive dysfunction, functional disabilities, falls and fractures, chronic pain, polypharmacy, depression, and urinary incontinence [19]. There are two main types of diabetes: Type 1 and Type 2, as well as other less common forms such as gestational diabetes.

Type 1 diabetes is an autoimmune condition in which the immune system mistakenly attacks and destroys the insulin-producing beta cells in the pancreas. The exact cause is still not fully understood. Typically diagnosed in children and young adults, although it can occur at any age. It requires lifelong insulin therapy through injections or an insulin pump. Frequent blood glucose monitoring is essential to adjust insulin doses and maintain blood sugar within target ranges. If not managed well, Type 1 diabetes can lead to complications such as heart disease, kidney disease, eye problems, and nerve damage.

Type 2 diabetes is characterized by insulin resistance, where the body's cells do not respond effectively to insulin, and by decreased insulin production over time. It is typically diagnosed in adulthood, but increasingly found in children and adolescents due to rising obesity rates. Management of type 2 may involve lifestyle changes (diet and exercise), oral medications, and, in some cases, insulin therapy. Regular blood glucose monitoring is often necessary to track glucose levels and adjust treatment as needed. Uncontrolled Type 2 diabetes can lead to complications similar to Type 1 diabetes, including cardiovascular disease, kidney disease, vision problems, and neuropathy.

Gestational diabetes occurs during pregnancy when the body cannot produce enough insulin to meet increased glucose needs. It is typically diagnosed during pregnancy and usually resolves after childbirth. Managed through dietary changes, exercise, and sometimes medication, such as insulin. Regular blood glucose monitoring is important during pregnancy to control glucose levels and reduce risks to both the mother and the baby. Gestational diabetes, if uncontrolled, can lead to complications during pregnancy and delivery, as well as an increased risk of Type 2 diabetes for both the mother and child in the future.

Diabetes, as a chronic disease, requires ongoing self-care and medical attention to maintain optimal health and prevent complications. Older adults with diabetes are at higher risk for both acute and chronic microvascular and macrovascular complications from the disease, including major lower-extremity amputations, visual impairments, myocardial infarctions, and end-stage renal disease [18]. Proper management can help individuals with diabetes lead fulfilling and healthy lives and avoid complications. Some key aspects to monitor for diabetes in the aging population are:

- ✓ *Blood Glucose Levels*: Regular monitoring of blood glucose levels is essential to manage diabetes. This can be done through self-monitoring using a glucose meter or continuous glucose monitoring systems. It helps determine if blood sugar levels are within the target range or if adjustments in medication, diet, or physical activity are needed.
- ✓ *HbA1c Levels*: HbA1c is a blood test that provides an average of blood sugar levels over the past two to three months. Monitoring HbA1c levels helps assess long-term blood sugar control and the effectiveness of diabetes management strategies.
- ✓ *Blood Pressure:* High blood pressure is common in individuals with diabetes and can increase the risk of cardiovascular complications. Regular monitoring of blood pressure is important to ensure it is within a healthy range and to make necessary lifestyle modifications or medication adjustments if needed.
- ✓ *Cholesterol Levels*: Diabetes is associated with an increased risk of cardiovascular disease. Monitoring cholesterol levels, including LDL (bad) cholesterol and HDL (good) cholesterol, helps assess cardiovascular risk and guide appropriate interventions.

- ✓ *Kidney Function*: Diabetes can affect kidney function over time. Monitoring kidney function through regular blood and urine tests helps detect any signs of kidney damage and allows for early intervention.
- ✓ *Eye Health*: Diabetes can lead to eye complications such as diabetic retinopathy. Regular eye exams by an ophthalmologist or optometrist are important to detect and manage any diabetic eye problems.
- ✓ *Foot Health*: Diabetes can cause nerve damage and poor circulation, increasing the risk of foot problems. Regular foot examinations and proper foot care are essential to prevent complications such as ulcers or infections.
- ✓ Medications: As needed, medications such as insulin, oral hypoglycemic agents, or other injectable medications may be prescribed to control blood glucose levels.
- ✓ Lifestyle Changes: A healthy diet, regular physical activity, weight management, and avoidance of tobacco and excessive alcohol consumption are crucial.
- ✓ Education: Individuals with diabetes and their caregivers need education on the disease, its management, and how to prevent and recognize complications.

It is important for individuals with diabetes in the aging population to work closely with healthcare professionals, including endocrinologists, primary care physicians, and diabetes educators, to develop a personalized monitoring plan and receive appropriate guidance for managing their condition effectively with the help of ICT solutions.

2.3.4 Cognitive Impairment and Other Dementias

Cognitive impairment and dementia are related but distinct conditions that involve a decline in cognitive function. Cognitive impairment is a common problem in the aging population that is associated with age with an occurrence rate of approximately 21.5–71.3 per 1,000 person-years in older adults [20].

Cognitive Impairment is a condition in which an individual experiences mild to moderate difficulties with cognitive functions such as memory, attention, language, reasoning, and problem-solving [21]. Usually it results from various factors, including age-related changes in the brain, medical conditions (e.g., thyroid disorders), medication side effects, and lifestyle factors (e.g., alcohol or drug use). Cognitive impairment is typically milder than dementia. It may not interfere significantly with an individual's ability to perform daily activities independently. While some cases of cognitive impairment remain stable or improve with treatment or lifestyle changes, others may progress to more severe cognitive decline or dementia.

Dementia is a more severe and progressive decline in cognitive function that interferes significantly with an individual's ability to perform daily activities [22]. It is a syndrome rather than a specific disease, as it can be caused by various underlying conditions. Dementia can be caused by several underlying diseases and conditions. Alzheimer's disease is the most common cause of dementia, followed by vascular dementia, Lewy body dementia, and frontotemporal dementia, among others [23]. Dementia is characterized by memory loss, impaired judgment, language difficulties, changes in personality and behavior, and the inability to recognize familiar people and places [24]. These symptoms are often severe and progressive. Dementia has a profound impact on an individual's life, leading to a loss of independence and requiring significant caregiving and support. Dementia is generally a progressive condition, meaning that cognitive function continues to deteriorate over time. The rate of progression varies depending on the underlying cause and the individual. While there is no cure for most forms of dementia, there are treatments and interventions that can help manage symptoms, slow progression, and improve the quality of life for affected individuals.

Cognitive impairment and dementia have a profound and multifaceted impact on the aging population, affecting individuals, their families, and society as a whole. They often result in a loss of independence for older adults. As their cognitive function declines, they may struggle to perform basic activities of daily living, such as dressing, bathing, and preparing meals, leading to increased dependence on caregivers [25]. These conditions can significantly diminish an individual's quality of life. Memory loss, confusion, and the inability to recognize loved ones or familiar surroundings can cause frustration, anxiety, and depression. Individuals with cognitive impairment and dementia frequently require extensive healthcare services, including frequent doctor visits, hospitalizations, and specialized care. This places a strain on healthcare systems and resources. Cognitive impairment and dementia can lead to social isolation. Individuals may withdraw from social activities and lose touch with friends and loved ones, which can exacerbate feelings of loneliness and depression.

Monitoring older adults with cognitive impairment and dementia is essential to ensure their well-being, safety, and quality of life [26]. The key aspects to monitor are:

- ✓ Regular assessment of cognitive function using standardized tools like the Mini-Mental State Examination (MMSE) or the Montreal Cognitive Assessment (MoCA). This helps track changes in memory, attention, language, and problem-solving abilities over time.
- ✓ Monitoring an individual's ability to perform essential Activities of Daily Life ADLs independently, such as bathing, dressing, grooming, toileting, eating, and mobility. Declines in these areas may require additional assistance.
- ✓ Monitoring Instrumental Activities of Daily Living (IADLs): Evaluate an individual's capacity to manage more complex tasks, including meal preparation, managing medications, using transportation, managing finances, and performing household chores.
- ✓ Keeping track of changes in behavior, mood, and psychological symptoms such as agitation, aggression, depression, anxiety, hallucinations, or delusions. These symptoms may require intervention or medication adjustments.
- ✓ Ensuring a safe living environment by assessing and addressing potential hazards, such as loose rugs, clutter, or unsafe appliances. Install safety measures like grab bars and handrails and consider a wander alarm or door locks if wandering is a concern.

- ✓ Nutrition and Hydration: Monitor the individual's eating and drinking habits to ensure they are getting proper nutrition and hydration. Weight loss, dehydration, and malnutrition are common concerns.
- ✓ Medication Management: Check that medications are being taken as prescribed and monitor for any side effects or adverse reactions. Consider using pill organizers or medication management devices to help with adherence.
- ✓ Medical Conditions: Stay vigilant about the management of chronic medical conditions such as diabetes, hypertension, and heart disease, as individuals with dementia may have difficulty following treatment plans independently.
- ✓ Fall Risk: Assess and address fall risks by maintaining a clutter-free environment, providing mobility aids if needed, and conducting regular balance assessments.
- ✓ Social Engagement: Encourage social interaction and monitor for signs of social isolation, as maintaining a social network is crucial for emotional well-being.
- ✓ Pain and Discomfort: Be vigilant for signs of pain or discomfort, as individuals with cognitive impairment may have difficulty expressing their physical needs. Look for non-verbal cues, changes in behavior, or physical indicators of discomfort.

Regular communication with healthcare providers and specialists, such as geriatricians or neurologists, can provide valuable guidance in monitoring and managing cognitive impairment and dementia. Additionally, involving support groups and community resources can help provide a network of assistance for both the individual and their caregivers.

It's important to note that cognitive impairment can be a transitional stage or an early sign of dementia, but not all individuals with cognitive impairment will develop dementia. Accurate diagnosis and evaluation by healthcare professionals are crucial for determining the underlying cause and appropriate management strategies for both cognitive impairment and dementia.

In conclusion, cognitive impairment and dementia have far-reaching consequences for older adults and their communities. Addressing the impact of these conditions requires a multifaceted approach, including improved diagnosis, better support for caregivers, increased public awareness, and ongoing research efforts to develop effective treatments and interventions with the support of ICT solutions. It is crucial to prioritize the well-being and dignity of those affected by cognitive impairment and dementia as the global population continues to age.

2.3.5 Stroke

Three quarters of all new stroke events occur in people aged 65 years and older [27]. A stroke occurs when there is a sudden interruption in the blood supply to the brain. This can happen due to a blockage, ischemic stroke, [28] or bleeding in the brain, hemorrhagic stroke. Approximately 87% of all strokes are ischemic strokes [27]. A stroke is a medical emergency and requires immediate treatment to minimize brain damage and improve outcomes. Risk factors for stroke include hypertension, smoking, diabetes, high cholesterol, and heart disease.

Stroke risk increases with age. The aging process itself can contribute to factors like arterial stiffness and the accumulation of risk factors over time. Older adults are more vulnerable to the effects of stroke because of age-related changes in the brain and body, including decreased brain reserve and slower recovery. Stroke can have devastating consequences for older individuals, affecting their independence, quality of life, and overall health [29].

- ✓ Stroke survivors, especially older ones, often experience impaired mobility. This can lead to difficulties with walking, balance, and coordination.
- ✓ Muscle weakness on one side of the body (hemiparesis) is common after a stroke, which can affect daily activities.
- ✓ Post-stroke fatigue is prevalent and can limit an older person's ability to engage in physical activities.
- ✓ Stroke can lead to cognitive impairment, including memory problems, difficulty concentrating, and even dementia in some cases.

- ✓ Many stroke survivors, including the elderly, may experience depression, anxiety, or emotional lability (rapid mood swings).
- ✓ Stroke often requires ongoing care and support. Family members may take on the role of caregivers, leading to increased stress and caregiver burden.
- ✓ Preventing strokes is crucial. This includes managing risk factors through lifestyle changes, medications, and regular medical check-ups.

Stroke is a chronic disease that disproportionately affects the aging population due to age-related risk factors. Its impact on older individuals is substantial, affecting physical, cognitive, emotional, and social aspects of their lives. Preventive measures, early intervention, and ongoing support are essential for managing stroke and improving the well-being of the aging population.

Preventing strokes in older adults involves proactive monitoring and management of various risk factors [30]. Here are key aspects to monitor to reduce the risk of strokes in older individuals:

- ✓ High blood pressure (hypertension) is a major risk factor for strokes. Regular monitoring of blood pressure is crucial.
- ✓ Regularly monitor cholesterol levels and work with a healthcare provider to manage them through diet, exercise, and medication if necessary.
- ✓ Diabetes is a significant risk factor for strokes. Monitor blood sugar levels and manage diabetes through medication, diet, exercise, and regular medical check-ups.
- ✓ Smoking significantly increases stroke risk. Encourage older adults to quit smoking and avoid exposure to secondhand smoke.
- ✓ Maintaining a healthy weight is essential for stroke prevention. Monitor weight and BMI and promote a balanced diet and regular physical activity.
- ✓ If an older adult is prescribed medications to manage risk factors such as hypertension, diabetes, or high cholesterol, ensure they take their medications as prescribed and follow up with healthcare providers as needed.

- ✓ Excessive alcohol consumption can raise blood pressure and contribute to stroke risk. Encourage moderation or abstinence from alcohol, especially if there is a history of alcohol-related issues.
- ✓ Atrial Fibrillation (AFib) is a heart rhythm disorder that increases the risk of stroke. Monitor for signs of AFib, such as irregular heartbeat, and seek medical attention if detected.
- ✓ Sleep apnea is associated with an increased risk of stroke. If an older adult exhibits symptoms like loud snoring or daytime sleepiness, consider evaluation and treatment for sleep apnea.
- ✓ Chronic stress can contribute to high blood pressure and other risk factors for stroke. Encourage stress-reduction techniques such as relaxation exercises, meditation, or counseling.
- ✓ Older adults should also be monitored for their risk of falls, as falls can result in head injuries and increase the risk of stroke. Implement fall prevention strategies, such as home safety modifications and balance exercises.

Regular monitoring of these factors and proactive management can significantly reduce the risk of strokes in older adults. It is essential for healthcare providers, caregivers, and the individuals themselves to work together to implement a comprehensive stroke prevention plan with the support of ICT solutions.

2.3.6 Falls and Near Falls

Falls are a prevalent issue in the geriatric population and can result in damaging physical and psychological consequences. Each year approximately 28-35% of people aged 65 and over fall worldwide increasing to 32-42% for those over 70 years of age. The frequency of falls increases with age and frailty level. A study in the Middle East region found that 40% of older adults aged 65 and above fell each year in Lebanon [11]. Falls are caused by an interaction of a number of risk factors. The more the comorbidities between these factors, the greater is the risk of falling. According to the World Health Organization (WHO), the risk factors for falling among older adults are categorized into three categories: aging related changes, pathological factors, and extrinsic factors [31].

- ✓ Age related changes are muscle weaknesses, sedentary behavior, loss of mobility, gait disturbances, and decline in sensory functions.
- ✓ Pathological factors are cardiovascular disorders, neurological disorders, Parkinson’s disease, Vertigo, musculoskeletal disorders, cognitive impairment, dementia, and medications.
- ✓ Extrinsic factors could be environmental hazards such as slippery floors, uneven surfaces, footwear, or clothing problems.

Falls can result in lasting and critical consequences, including injuries, long term disability, reduced activity and mobility levels, admission to long term care institutions, fear of falling, reduced self-confidence in mobility, and death [11] [31].

Preventing falls among the aging population is crucial for maintaining their health, independence, and quality of life. Monitoring and implementing fall prevention strategies can significantly reduce the risk of falls in older adults. Some steps to monitor and prevent falls among the aging population [32]:

- ✓ Perform a comprehensive assessment of each older adult's fall risk factors. This assessment can be performed by healthcare providers, such as doctors, nurses, or physical therapists.
- ✓ Review the older adult's medications for any that may cause dizziness, drowsiness, or balance issues. Consult with a healthcare provider to adjust or change medications if necessary.
- ✓ Regular eye check-ups are essential to ensure that older adults have the correct eyeglasses and that their vision is optimal for fall prevention.
- ✓ Conduct a home safety evaluation to identify and rectify potential hazards, such as loose rugs, slippery floors, poor lighting, and clutter.
- ✓ Assess the older adult's strength and balance. This can be done through physical therapy or balance exercises to improve muscle tone and coordination.

- ✓ Provide assistive devices like canes or walkers to help with mobility and balance. Ensure these devices are properly fitted and maintained.
- ✓ Encourage the use of appropriate footwear with good traction and arch support. Discourage the use of high heels or shoes with slippery soles.
- ✓ Promote regular exercise, including strength training and balance exercises, to improve muscle strength and stability.
- ✓ Ensure that older adults are maintaining a well-balanced diet and staying hydrated to prevent dizziness and weakness.
- ✓ Promote bone health through adequate calcium and vitamin D intake. Discuss the need for bone density testing and osteoporosis prevention with healthcare providers.
- ✓ Older adults should be educated about the importance of being vigilant for environmental hazards in their surroundings, especially when in unfamiliar places.
- ✓ Encourage regular check-ups with healthcare providers to *monitor and manage chronic conditions, as well as assess fall risk*.
- ✓ Provide education on fall prevention, including tips on how to get up safely after a fall and what to do in case of a fall.
- ✓ Consider using fall detection alarms or monitoring systems, especially for older adults at high risk of falls who live alone.

Fall prevention is an ongoing process, and the strategies should be tailored to the individual's specific risk factors and needs. Regular reassessment and adjustments to the prevention plan are essential as an older adult's health and circumstances change over time with the support of ICT solutions.

2.4 Conclusion

Encountering an increase in the older population with limitations in the availability of specialized caregivers, healthcare providers are starting to offload certain parts of the healthcare-pathways to artificial intelligence (AI) by applying smart information and communication s technology (ICT) solutions for social care concerning diseases in old age. AI can now be found in every step of the healthcare pathway, ranging from intelligent tracking of biometric information to early diagnosis of diseases. AI is helping older patients, and their families understand the treatment pathways. AI is also helping clinicians to treat the conditions more efficiently. Such technologies include very sophisticated and quite simple ICT solutions like smart home systems, applications in the field of tele-health, reminder functions, fall detection and prevention systems, videophones, video games and a lot more [33].

The aging of the population and the onset of chronic diseases are interconnected. The development of ICT solutions can improve the quality of life (QoL) of older adults by supporting independent living at home while reducing health and social expenses. Therein lies the motivation of this research, i.e., the development of health-related ICT solution with the purpose of prolonging and providing aid for the independent and active living of older adults in their homes with the intent of satisfying the needs of older adults and caregivers, improve well-being and QoL, and being affordable in terms of cost [33].

There are many proposed health-related ICT solutions of smart homes for the aging population that are used in the context of patient activity monitoring [34] [35] [36, 37], health monitoring and/or managing [38] [39] [40]. These solutions give older adults the opportunity to use wearables and/or environmental sensors and devices which are intended to monitor and/or manage various health conditions related to the World Health Organization (WHO)'s top 10 chronic diseases that are behind the most deaths globally.

Different technologies are used to build ICT solutions with user friendly configuration and management that can be integrated with smart environments at home, social community, etc. These technologies include various functions, which can be controlled by sensors and devices, communication and connectivity, and cloud and analytics and integrated with the living environments to support the individual needs and independence [41]. With this approach they can improve the coordination among caregivers, emergency response teams, and intervention effectiveness, which contributes to cost savings and better QoL for older adults living with chronic conditions. A detailed presentation of ICT solutions for healthcare systems is available in *Chapter 3*.

References

[1] J. G. O. William R. Hazzard, Principles of Geriatric Medicine and Gerontology. 1990.

[2] J. E. Morley, "The top 10 hot topics in aging," J. Gerontol. A, Biol. Sci. Med. Sci., vol. 59, no. 1, pp. M24–M33, 2004.

[3] W. H. Organization, "WHO Global Report on Falls Prevention in Older Age," World Health Organization, Geneva, Switzerland, 2008.

[4] W. H. Organization, "Falls," ed: WHO, 2018.

[5] P. Couturier, "Place de l'actimétrie dans la gestion médicale du sujet âgé fragile," Gérontologie et Soc., vol. 2, pp. 13–23, 2005.

[6] G. I. P. A. M. Herghelegiu, A. M. Marin and R. M. Nacu, "Risk Factors and Prevention Strategies4,r Falls in Elderly," The 5th IEEE International Conference on E-Health and Bioengineering, pp. 1-4,, 2015, doi: 10.1109/EHB.2015.7391398.

[7] M. E. Tinetti, M. Speechley, and S. F. Ginter, "Risk-Factors for Falls among Elderly Persons Living in the Community," (in English), New Engl J Med, vol. 319, no. 26, pp. 1701-1707, Dec 29 1988, doi: Doi 10.1056/Nejm198812293192604.

[8] M. Montero-Odasso, J. Verghese, O. Beauchet, and J. M. Hausdorff, "Gait and cognition: a complementary approach to understanding brain function and the risk of falling," J Am Geriatr Soc, vol. 60, no. 11, pp. 2127-36, Nov 2012, doi: 10.1111/j.1532-5415.2012.04209.x.

[9] R. A. Sibai AM, Kronfol KM, "Ageing in the Arab Region: Trends, Implications and Policy options," The United Nations Population Fund (UNFPA), Economic and Social Commission of Western Asia (ESCWA) and the Center for Studies on Aging (CSA). 2014.

[10] R. A. Mehio Sibai A, Kronfol NM., "Aging in Lebanon: Perils and prospects," J Med Liban, pp. 63 (1): 2-7, 2015.

[11] A. Kalache et al., "World Health Organisation Global Report on Falls Prevention in Older Age," World Health Organization, Geneva, 2007. [Online]. Available: http://www.who.int/ageing/publications/Falls_prevention7March.pdf.

[12] K. N. Sibai AM, "Older population in Lebanon: Facts and prospects," Center for

Studies on Aging (CSA) and the United Nations Population Fund (UNFPA), 2011.

[13] A. Aïdoud et al., "High Prevalence of Geriatric Conditions Among Older Adults With Cardiovascular Disease," Journal of the American Heart Association, vol. 12, no. 2, pp. e026850, 2023. doi: 10.1161/JAHA.122.026850.

[14] F. Sanchis-Gomar, C. Perez-Quilis, R. Leischik, and A. Lucia, "Epidemiology of coronary heart disease and acute coronary syndrome," Annals of translational medicine, vol. 4, no. 13, p. 256, 2016. doi: 10.21037/atm.2016.06.33.

[15] R. Hervás, J. Fontecha, D. Ausín, F. Castanedo, J. Bravo, and D. López-De-Ipiña, "Mobile Monitoring and Reasoning Methods to Prevent Cardiovascular Diseases," Sensors, vol. 13, pp. 6524-6541, 2013.

[16] C. Pedone, D. Chiurco, S. Scarlata, and R. A. Incalzi, "Efficacy of multiparametric telemonitoring on respiratory outcomes in elderly people with COPD: A randomized controlled trial," BMC Health Serv. Res., vol. 13, p. 82, 2013.

[17] L. Lahousse et al., "Risk of Frailty in Elderly With COPD: A Population-Based Study," The Journals of Gerontology: Series A, vol. 71, no. 5, pp. 689-695, May 2016. doi: 10.1093/gerona/glv154.

[18] E. Leung, S. Wongrakpanich, and M. N. Munshi, "Diabetes Management in the Elderly," Diabetes spectrum: a publication of the American Diabetes Association, vol. 31, no. 3, pp. 245-253, 2018. doi: 10.2337/ds18-0033.

[19] M. Munshi, "Managing the 'geriatric syndrome' in patients with type 2 diabetes," The Consultant pharmacist: the journal of the American Society of Consultant Pharmacists, vol. 23, Suppl B, pp. 12-16, 2008.

[20] S. A. Eshkoor, T. A. Hamid, C. Y. Mun, and C. K. Ng, "Mild cognitive impairment and its management in older people," Clinical Interventions in Aging, vol. 10, pp. 687-693, 2015. doi: 10.2147/CIA.S73922.

[21] H. J. Woodford and J. George, "Cognitive assessment in the elderly: a review of clinical methods," QJM: monthly journal of the Association of Physicians, vol. 100, no. 8, pp. 469–484, 2007. doi: 10.1093/qjmed/hcm051.

[22] B. L. Plassman et al., "Prevalence of dementia in the United States: the aging, demographics, and memory study," Neuroepidemiology, vol. 29, no. 1-2, pp. 125-132, 2007.

[23] H. Grossman, C. Bergmann, and S. Parker, "Dementia: a brief review," The Mount Sinai Journal of Medicine, New York, vol. 73, no. 7, pp. 985-992, Nov 2006. PMID: 17195884.

[24] M. Subramaniam et al., "Prevalence of dementia in people aged 60 years and above: results from the WiSE study," Journal of Alzheimer's Disease, vol. 45, no. 4, pp. 1127-1138, 2015.

[25] Y. E. Geda, "Mild cognitive impairment in older adults," Current psychiatry reports,

vol. 14, pp. 320-327, 2012.

[26] M. Lussier et al., "Early detection of mild cognitive impairment with in-home monitoring sensor technologies using functional measures: a systematic review," IEEE journal of biomedical and health informatics, vol. 23, no. 2, pp. 838-847, 2018.

[27] R. Bonita, N. Solomon, and J. B. Broad, "Prevalence of stroke and stroke-related disability: estimates from the Auckland Stroke Studies," Stroke, vol. 28, no. 10, pp. 1898-1902, 1997.

[28] M. Yousufuddin and N. Young, "Aging and ischemic stroke," Aging, vol. 11, no. 9, pp. 2542-2544, 2019. doi: 10.18632/aging.101931

[29] S. K. Lui and M. H. Nguyen, "Elderly Stroke Rehabilitation: Overcoming the Complications and Its Associated Challenges," Current gerontology and geriatrics research, vol. 2018, article 9853837, 2018. doi: 10.1155/2018/9853837.

[30] C. Samuthpongtorn, T. Jereerat, and N. C. Suwanwela, "Stroke risk factors, subtypes and outcome in elderly Thai patients," BMC neurology, vol. 21, no. 1, p. 322, 2021. doi: 10.1186/s12883-021-02353-y.

[31] C. Todd and D. Skelton, "What are the main risk factors for falls amongst older people and what are the most effective interventions to prevent these falls?," World Health Organization. Regional Office for Europe, 2004. [Online]. Available: https://iris.who.int/handle/10665/363812.

[32] L. D. Gillespie et al., "Interventions for preventing falls in older people living in the community," The Cochrane database of systematic reviews, vol. 2012, no. 9, p. CD007146, 2012. doi: 10.1002/14651858.CD007146.pub3.

[33] S. F. D. Pal, N. Charoenkitkarn, and P. Kanthamanon, "Internet-of-Things and Smart Homes for Elderly Healthcare: An End User Perspective," IEEE Access, vol. 6, pp. 10483-10496, 2018.

[34] E. H. L. Magnusson, "Supporting frail older people and their family carers at home using information and communication technology: cost analysis," Journal of Advanced Nursing, vol. 51, no. 6, pp. 645-657, 2005.

[35] G. Sacco et al., "Detection of activities of daily living impairment in Alzheimer's disease and mild cognitive impairment using information and communication technology," Clin Interv Aging, vol. 7, pp. 539-549, 2012. doi: 10.2147/CIA.S36297.

[36] R. W. Frank Rudzicz, M. Begum, and A. Mihailidis, "Speech Interaction with Personal Assistive Robots Supporting Aging at Home for Individuals with Alzheimer's Disease," ACM.

[37] C. L. A. Lotfi, S. M. Mahmoud, and M. J. Akhlaghinia, "Smart homes for the elderly dementia sufferers: Identification and prediction of abnormal behaviour," Ambient Intell. Humanized Computing, vol. 3, pp. 205-218, 2012.

[38] M. A. F. Cavallo and M. Arvati, "An ambient assisted living approach in designing

domiciliary services combined with innovative technologies for patients with Alzheimer’s disease: A case study," American Journal of Alzheimer's Disease & Other Dementias, vol. 30, pp. 69-77, 2015.

[39] A. J. Jara, M. A. Zamora, and A. F. G. Skarmeta, "An internet of things–based personal device for diabetes therapy management in ambient assisted living (AAL)," Pers Ubiquit Comput, vol. 15, pp. 431-440, 2011.

[40] S. Muuraiskangas et al., "V2me: Evaluating the first steps in mobile friendship coaching," Journal of Ambient Intelligence and Smart Environments, vol. 4, no. 6, pp. 517-534, 2012.

[41] P. Maresova et al., "Health–Related ICT Solutions of Smart Environments for Elderly–Systematic Review," in IEEE Access, vol. 8, pp. 54574-54600, 2020, doi: 10.1109/ACCESS.2020.2981315.

Chapter 3: Directing and Orienting ICT Healthcare Solutions to Address the Needs of the Aging Population

A version of this chapter has been published in MDPI Healthcare Journal with the title: “Directing and Orienting ICT Healthcare Solutions to Address the Needs of the Aging Population”.

N. Fares, R.S. Sherratt, and I.H. Elhajj, "Directing and Orienting ICT Healthcare Solutions to Address the Needs of the Aging Population," Healthcare, vol. 9, p. 147, 2021. [Online]. Available: https://doi.org/10.3390/healthcare9020147.

With an aging population, it is essential to maintain good health and autonomy for as long as possible. Instead of hospitalization and institutionalization, older people with chronic conditions can be assisted in their own home with numerous “smart” devices that support them in their activities of daily living, manage their medical conditions, and prevent fall incidents. Information and Communication Technology (ICT) solutions facilitate the monitoring and management of older people’s health to improve quality of life and physical activity with a decline in caregivers’ burden. Method: The aim of this paper was to conduct a systematic literature review to analyze the state of the art of ICT solutions for older people with chronic conditions, and the impact of these solutions on their quality of life from a biomedical perspective. Results: By analyzing the literature on the available ICT proposals, it is shown that different approaches have been deployed by noticing that the more cross-interventions are merged then the better the results are, but there is still no evidence of the effects of ICT solutions on older people's health outcomes. Furthermore, there are still unresolved ethical and legal issues. Conclusion: While there has been much research and development in healthcare ICT solutions for the aging population, ICT solutions still need significant development in order to be user-oriented, affordable, and to manage chronic conditions in the aging wider population.

3.1 Introduction

Aging is an instinctive, disruptive, and wide-ranging process for every individual. Aging is a process distinguished by different morphological, pathophysiological, psychological, social, and environmental aspects. All these aspects of aging are inspected in "gerontology". Social and cultural gerontology has symbolized the assumption of aging as a biomedical process while focusing on the contextual factors that mold the practices and patterns of aging [1]. The age of the person is assessed in each aspect by their functional abilities. Therefore, a person's health status is the consequence of the accumulative effects of aging in addition to the obtained disease. This aging situation leads the person to a state of "unstable incapacity" for "normal aging" [2].

The aging process is specified in older people by a decreased reaction to the environment as well as to definite pathologies accompanied by an obvious decrease in individualism and incorporation in activities of daily living (ADL). The aging process affects various systems in the human body, such as the nervous system, sensory system, cardiovascular system, metabolic system, respiratory system, and musculoskeletal system. The observed effects of the aging process are more visible in the musculoskeletal system in older people in terms of mobility and locomotion [3].

Each year, 37.3 million falls are encountered among older people aged 65 and above. This makes older people more vulnerable to fatal falls that require medical care [4]. Although falls are unavoidable in nature, it is possible to detect, manage, and even prevent them from occurring by means of proper administration of human and technical interventions. This dual embrace between gerontology and technology is regarded as "gerontechnology". The after effect of this routine is to be recognized in terms of an increase in independence and an improvement in the quality of life of older people [5]. This indicates the importance of science and the design and use of technology in the development of ICT solutions that focus on user involvement, viewing the older person as an agent that creates and develops meaning for later life as they interact with technology [1].

However, the health of older people is known to be heterogeneous in nature. Heterogeneity in the health of older people is such that differences among people of the same age may be greater than those inferred from chronological age differences, based on the number of years a person has been alive.

There are different factors affecting the health outcomes of older people. These factors can be biomedical (e.g., genetic), socioeconomic, or behavioral, such as exercise, nutrition, social engagement and support, stress levels, and geographic location. In this research, we focus on the biomedical perspective of aging excluding other factors of heterogeneity affecting the health of older people.

Therefore, the use of ICT solutions is limited to older people with chronic diseases. The involvement of this group of older people in the creation of ICT healthcare solutions allows for the development of solutions which are personalized. The challenge here for researchers is to find the tools and channels to innovate approaches and technologies focusing on the user-centered needs of older users with chronic diseases [1].

Several smart ICT solutions have already been commercially distributed. Such solutions include all electronic products that deal with information in a digital form as storing, processing, transmitting, converting, duplicating, or retrieving electronic information. Examples of ICT solutions are communication devices or applications as radio, television, computer network, satellite system, the internet, smartphones, and personal digital assistants (PDA). ICT systems in the healthcare sector for older people monitor and manage various aspects of the aging process in older adults. Common aspects of the aging process from a biomedical perspective include hearing loss, musculoskeletal deterioration causing falls and near-falls, chronic obstructive pulmonary disease, heart disease, diabetes, and dementia. Older adults are more likely to experience more than one condition at the same time.

The monitoring and management process of the different aspects of aging is carried out through using different kinds of sensors to capture motion data, biological data, and environmental data for more in-depth data analysis and processing. Falls and the resulting injuries encountered in the aging population manifest their occurrence due to aging, chronic disease-related medical conditions, and the older people's interactions with their social and physical environments [6]. Falling risk escalates when multiple risk factors are interconnected [7]. This confirms the need for healthcare-monitoring ICT solutions for older people that manage their health and consequently prevent health decline and falls and detect near-fall events.

Other aspects of the aging process such as natural cognitive and psychical decline are also monitored and managed using ICT solutions addressing different chronic diseases. The cognitive and physical decline in turn impacts the functional abilities and increases the risk of falls and near-falls in the aging population [8]. This imposes new challenges on the socioeconomical level of the increased demographic change in the population. These new challenges pinpoint the need for appropriate management of older people's health to reduce the impact of unavoidable aging and its corresponding fallouts.

The aging of the population and the onset of chronic diseases are interconnected. The development of ICT healthcare solutions impacts the quality of life (QoL) of older people through serving independent living at home as well as eliminating health and social expenses in the aging population. Thus, the innovation of this paper lies in the analysis of health-related ICT solutions with the aim of identifying their effectiveness in encouraging active and independent living of older people at home, satisfying the needs of the older people and their caregivers, improving their wellbeing and QoL, and making it affordable [9].

There are many proposed health-related ICT solutions for the aging population. Such solutions are used in the framework of monitoring older people's activities [10–12] or monitoring and managing their health [13–15]. These solutions make it possible for the older person to use wearable sensors, environmental sensors, and devices that are devoted to monitoring and/or managing their health conditions in relation to the top ten chronic diseases causing death globally, as identified by the World Health Organization (WHO) [16], as presented in ***Figure 3.1***. Multiple factors contribute to mortality in older people.

To predict mortality in older people, different characteristics such as the obtained chronic disease, functional abilities, and personal characteristics of the older person need to be identified and analyzed. This review is limited to a biomedical perspective and does not focus on environmental and socioeconomical factors such as pollution, chemical exposure, social isolation, sex, and unhealthy habits causing mortality in the older population.

Various technologies are adopted in the assembly of ICT solutions with different characteristics such as user-friendly configuration, smart home integrated management, and social community. To support the older person's needs and independence of the aging population, these technologies consist of sensor or device-controlled functions, communication and connection methods, a cloud, and analytics integrated into the living environment of the older person [17]. Using this methodology, better coordination between caregivers, emergency response teams, and intervention can be achieved. This approach serves to reduce costs and improve QoL for older people having chronic medical conditions.

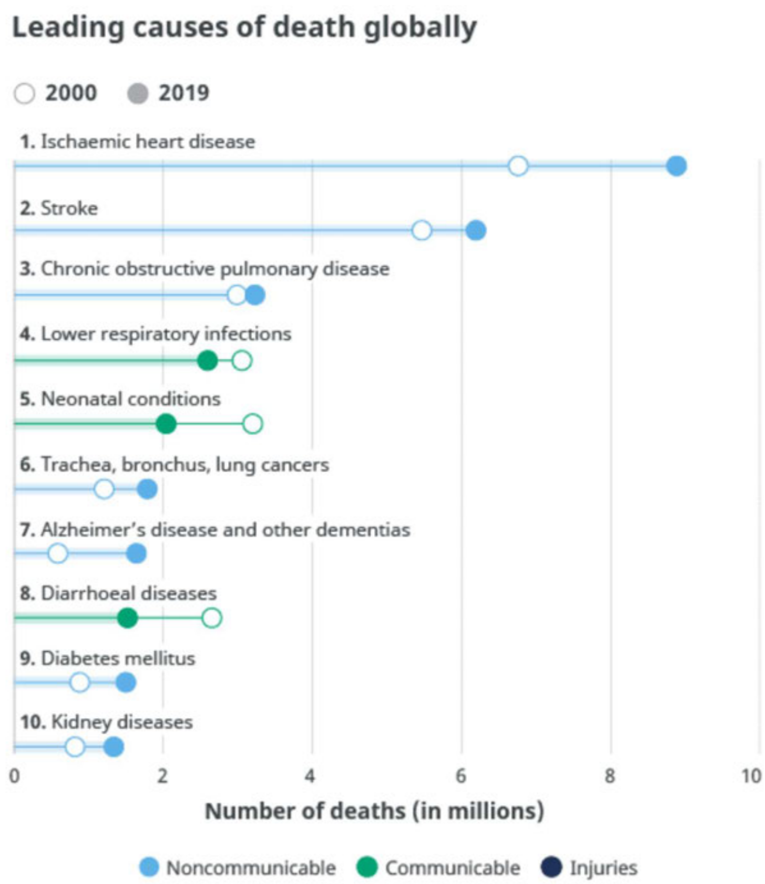

Figure 3.1: Chronic diseases causing death—top 10 global causes of death, 2016 [16].

In this review, it is concluded that older people do accept smart home technologies if they permit their independent living in their own environment. Older people's perceptions of ICT solutions at home have emerged from their belief that such technologies could invest in various aspects of independent living. Such aspects include providing support in emergency situations, assistance with medical conditions as hearing and visual impairment, detection and prevention of falls and near-falls, monitoring of physiological specifications as blood pressure and glucose level, assurance of older persons' safety and the security of their living environment, and finally providing a reminder system for appointments and medication and contradictions, if any [18].

This review considers the current state of the art of the available ICT solutions for healthcare monitoring in older people. Different categories of ICT solutions with different approaches for healthcare monitoring of older people are presented to reflect the available gaps and hypothesis requirements to be present in future ICT solutions for older people's healthcare management. Section 2 discusses different ICT categories, development processes, and architectures applied in healthcare. Section 3 provides a presentation of the state of the art in ICT healthcare solutions for assistive living in the aging population and presents the results of the review by evaluating different ICT solutions' readiness, acceptance by users, and effectivity in improving the older person's quality of living. Section 4 discusses the implications of the review and how ICT technologies can be improved to meet the needs of the aging population. Section 5 concludes the present study and offers future research directions.

3.2 ICT Solutions

In the field of healthcare advancement, ICT solutions may potentially play an important role in enhancing the quality of life of the aging population and allowing their independent living. Integrated ICT solutions assist in the healthy and safe aging of older people and minimize health and social expenses. They are greatly sustained in developed countries aiming to improve the quality of life (QoL), ensure the sustainability of care of its aging population, and pursue the demographic crisis through applying ICT solutions for home care in the context of old age-related chronic diseases [19].

3.2.1 ICT Health Monitoring Systems

3.2.1.1 Healthcare Monitoring and Management Architecture

Various healthcare ICT solutions have been investigated in this review. It was recognized that these solutions shared a common architecture and a similar set of properties. The common ICT solution architecture involved three tiers that collaborate to collect and analyze the sensory data of an older person. The tiers include consequently a set of sensors, a gateway, and a remote monitoring/management system. The different components of the tiers and how they collaborate are presented in ***Figure 3.2***. In this section, the progression of the common healthcare monitoring and management architecture is portrayed, and the deployed ICT technologies are described.

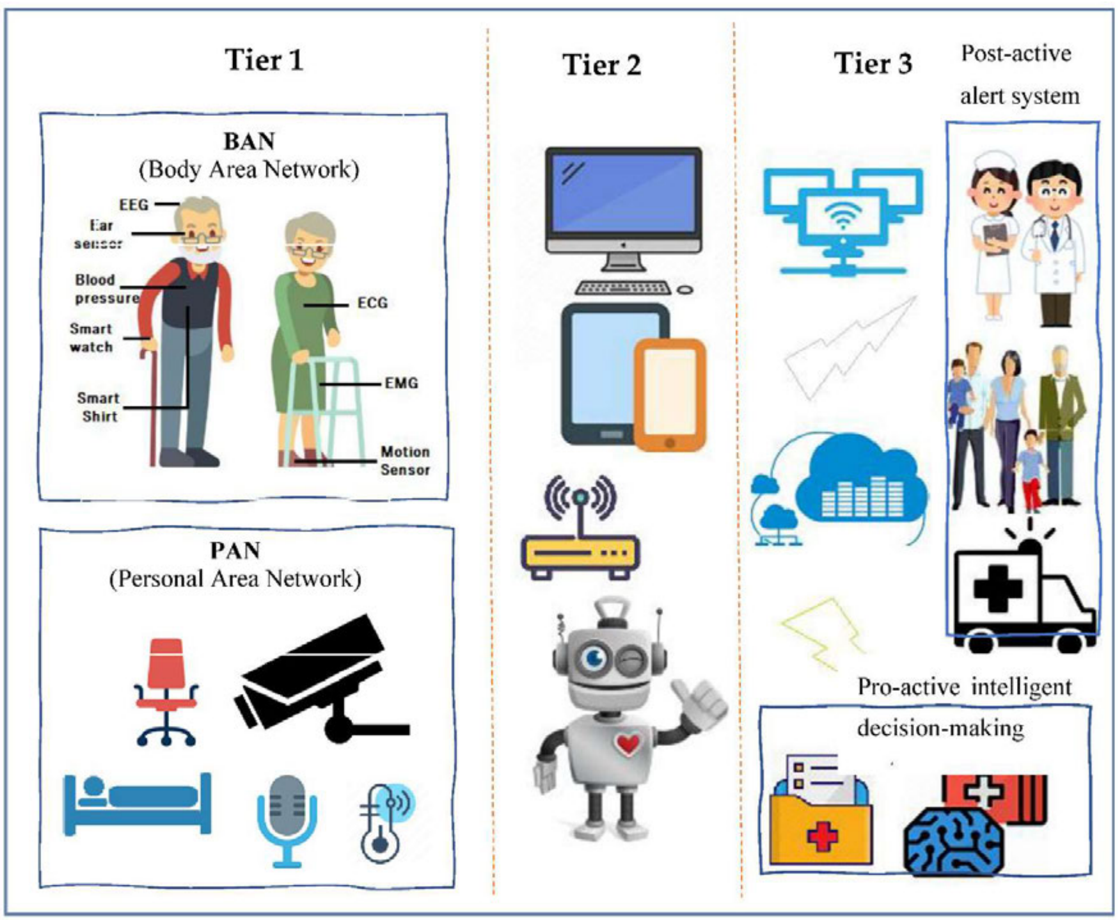

Figure 3.2: Common healthcare monitoring systems architecture.

Tier 1—Sensors

This tier is formed from various sensors that collect physiological, body motion, or environmental data. The sensors are devoted to the collection of signals attached to the Body Area Network (BAN) of the user and/or are arranged as a Personal Area

Network (PAN) or ambient sensors in the home of the user [21]. Sensors in a BAN are attached directly to the body of the older user, to his/her clothes, or implanted under the skin. BAN sensors constantly collect physiological signals from the older user. Such signals correspond to the temperature, heartbeat, physical activity, blood pressure, electroencephalography (EEG), electromyography (EMG), and electrocardiography (ECG) [22].

A PAN is developed of ambient sensors positioned on devices used by the older user. Such sensors provide rich contextual information about the user's activities and his/her living environment. Sound sensors, video cameras, RFID readers, pressure sensors, luminosity sensors, proximity sensors, pressure sensor, temperature sensors, humidity sensors, and location tracking sensors are examples of PAN sensors [22]. The extracted data from the sensors are in turn broadcasted to a local device using different methods.

Tier 2—Gateway

A gateway can be a customized device or a smartphone that is in the older user's living environment [22]. A gateway usually has the power of collecting data from sensors and dispatching them to a remote server placed either at the hospital or on a cloud to be analyzed. However, in later approaches, with the evolution of fog computing, analysis of the collected data is performed locally in the living environment of the older user for accelerated decision-making and better implementation of bandwidth where only partial data updates are transmitted to the cloud for further analysis or for historical recording.

Tier 3—Remote Monitoring, Feedback, and Decision-Making System

Monitoring, feedback, and decision-making are usually performed on a remote system (server) considered the core of the ICT system to which various data (physiological and environmental data) from sensors are transmitted [22]. Such a system has the following functionalities: (i) Operate specific algorithms on the collected data for further interpretation and analysis; (ii) Issue alerts in case of emergencies; (iii) Record every user's data to be stored in a database for future analysis as the prediction of undiagnosed diseases by applying data mining techniques; and iv) Offer a Graphical User Interface (GUI) to enable users (older people, caregivers, and clinicians) to monitor real-time health status.

3.2.1.2 Classification of ICT Healthcare Monitoring and Management Solutions

ICT healthcare monitoring and management systems are categorized into wearable based systems (WS), non-wearable-based systems (NWS), and fusion or hybrid-based systems (FS) [23]. The quantity and type of deployed sensors depends mainly on the context of the performed application, i.e., user's activity monitoring, older user's health monitoring and management, or both. Various types of sensors are assembled in wearable, non-wearable, and fusion systems.

Wearable System Sensors: Wearable system sensors consist of a collection of inertial and non-invasive sensors placed on the body of the older user. Wearable-based systems extensively use inertial sensors as accelerometers, gyroscope, inclinometer, barometers, and magnetometers to detect unexpected escalation in human gait, assess balance, and monitor displacement [24]. Inertial sensors are basically utilized for the identification of different causes of falls in the aging population, i.e., falls from sleeping, falls from sitting, falls caused by walking or standing, and falls caused by using supportive tools as a ladder, walker, or stairs [25]. For more precise monitoring in the context of fall prevention, more motion sensors are being placed on different body parts with the aim of measuring a wider range of characteristics of the human gait [26]. Such sensors are extensometers, force sensors, and goniometers. These sensors provide input linked to human locomotion such as extracting different gait characteristics and detecting abnormal gait behavior. On the other hand, intrinsic factors associated with the pathophysiological history of the older user as muscle fragility, diabetes, heart diseases, and hypertension can cause a change in the older user's behavior and may lead to a fall or near-fall [27]. Non-invasive healthcare sensors are deployed to collect healthcare data from the older user. Such healthcare data can be blood pressure, cortisol [28], agitation detection [29], and cardiac activity collected and measured using intrinsic sensors as infrared sensors, optical sensors, and oscillometers [30].

Non-Wearable System Sensors: Non-wearable system sensors consist of sensors deployed in the living environment of the older user. Such sensors serve privacy issues when obstructiveness is rejected by the older user. These systems have the aim of tracking user’s activities of daily living (ADL) and detecting unexpected changes in motion. However, the functionality of such solutions is limited to the sensor’s coverage range [31]. Sensors deployed in this category of systems are pressure, motion passive infrared (PIR), vibration, acoustic, and infrared sensors. These sensors are more appropriate for older people living at home and healthcare accommodations where falls are more likely to occur. According to the US Dept. of Health and Human Services [32], cognitive and physical decline in older people is inspected through the detection of a change in the behavior of the older user that is associated with gait deficits and subsequent falls. Non-wearable systems are correlated with identifying abnormalities, tracking any change in gait parameters, and detecting emergencies [23].

Fusion System Sensors: Various types of wearable and non-wearable sensors are interconnected in a hybrid sensing system to provide a multichannel source of data to be analyzed using single or multiple algorithms. Koshmak et al. [33] explained that the fusion of sensors can reasonably provide a significant improvement in fall-related systems in terms of reliability and specificity since the multisensory fusion approach meets the needs of older people living independently. The aim of deploying a fusion system for sensing is the flexibility of adjusting the system to a wider context such as a wider sensor network, implementation of fall detection and prevention strategies, designing a user-oriented monitoring and management process, and scalability. Currently, fusion systems are mainly utilized in human gait assessment labs with efforts to export such sensing technologies into the living environment of the older user, i.e., allowing ambient assisted living (AAL) for the aging population. A new ICT trend involves intelligent objects which are installed in the living environment of older people to support their independent living and the monitoring process. With all the advantages of fusion systems in the monitoring and management of older people's health, they still face some challenges such as permitting their integration into smart homes, performing real-time analysis, improving their computational power, and reducing their cost [23].

Smartphone sensing technologies are considered as either wearable or non-wearable technologies that are competent in sensing, processing, and communicating user's data while living in their own environment. These smartphone systems are either used as stand-alone sensing systems or are connected to other wearable or non-wearable sensors for more detailed monitoring and management of the older user's health as well as the detection and prevention of falls. Savenstedt et al. [21] declared that smartphone-based systems are still not yet deployed as stand-alone systems in a non-wearable context.

3.2.1.3 Data Processing Techniques in ICT Solutions

Data processing is a mechanism that includes the redeeming, remodeling, or categorizing of data. Data processing is mainly dependent on the volume of data, the complexity of the performed processing operations, the inbuilt technology of the operating system, and time restrictions. Examples of data processing techniques are data indexing, data mining, image processing, and video transcoding. Such techniques rely on the data parameters collected from different data sources. In different ICT solutions, i.e., wearable, non-wearable, or fusion ICT solutions, data parameters are extracted mainly from sensors. The data to be processed can be either human-generated as images, audio, or video files or machine-generated as log files generated by operating systems and network management log files, although processing is carried out by the machine. The data processed is either processed in patches when similar data are grouped and processed together or in real-time where data is processed immediately. ***Figure 3.3*** shows how artificial intelligence, machine learning, and data science are interconnected to provide data processing techniques that serve the accurateness of the processed data.

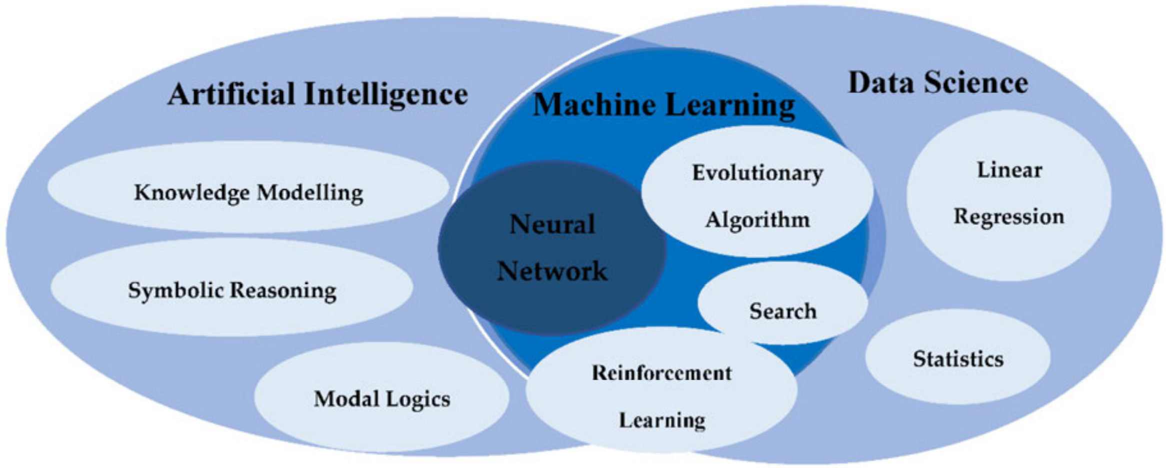

Figure 3.3: Data processing in ICT.

Artificial intelligence and data science are a broad domain of applications, systems, and more that target the replication of human intelligence through machines. To help computers learn automatically, artificial intelligence binds large amounts of data through iterative processing and intelligent algorithms. Artificial intelligence uses logic and decision trees. Data science deals with both structured and unstructured data and operates by sourcing, cleaning, and processing data to derive meaning out of them for analytical purposes.

Analytical methods (ANS) and machine learning methods (MLM) are methods used in data processing [23]. Analytical methods are derived from classic techniques which use statistical models to obtain clarification from data for prediction. Linear regression, time series, and transformations are examples of the analytical methods performed. ICT solutions based on ambient sensing systems use event sensing techniques. This sensing technique is carried out using vibrational data that are useful for the monitoring, tracking, and localization of the user of the system. ICT solutions with cameras perform image processing techniques. Different types of image processing methods are performed based on the requirements of the data to be collected. For example, to recognise the lying or standing posture of a user, spatiotemporal features of the user are extracted while in scene, i.e., the weight, skin color, ratio of silhouette height, width, and orientation of main body axis.

On the other hand, machine learning methods depend on complex algorithms to achieve a closer interpretation of the collected data with the aim of predicting output decisions as in neural networks. Neural networks allow the operating system to learn from observational data. Neural networks are considered one of the best machine learning methods since they address many challenges in image recognition, speech recognition, and natural language processing. As for camera-based fall detection ICT systems to achieve insight from the data for fall detection and even prediction, different methods that can be used are support vector machine (SVM) techniques as presented in Sakr et al. [34], Gaussian distribution of clustered knowledge, naïve Bayes, multilayer perceptron, and decision trees [29].

3.2.2 Different Categories of ICT Solutions

The range of ICT technologies varies between quite simple and very sophisticated ICT solutions, all having the common objective of improving the QoL of older people. Such ICT solutions can range from smart home systems and telehealth applications to reminder functions, fall detection/prediction/prevention systems, smartphones, etc. [35]. ***Figure 3.4*** gives the different categories of ICT solutions.

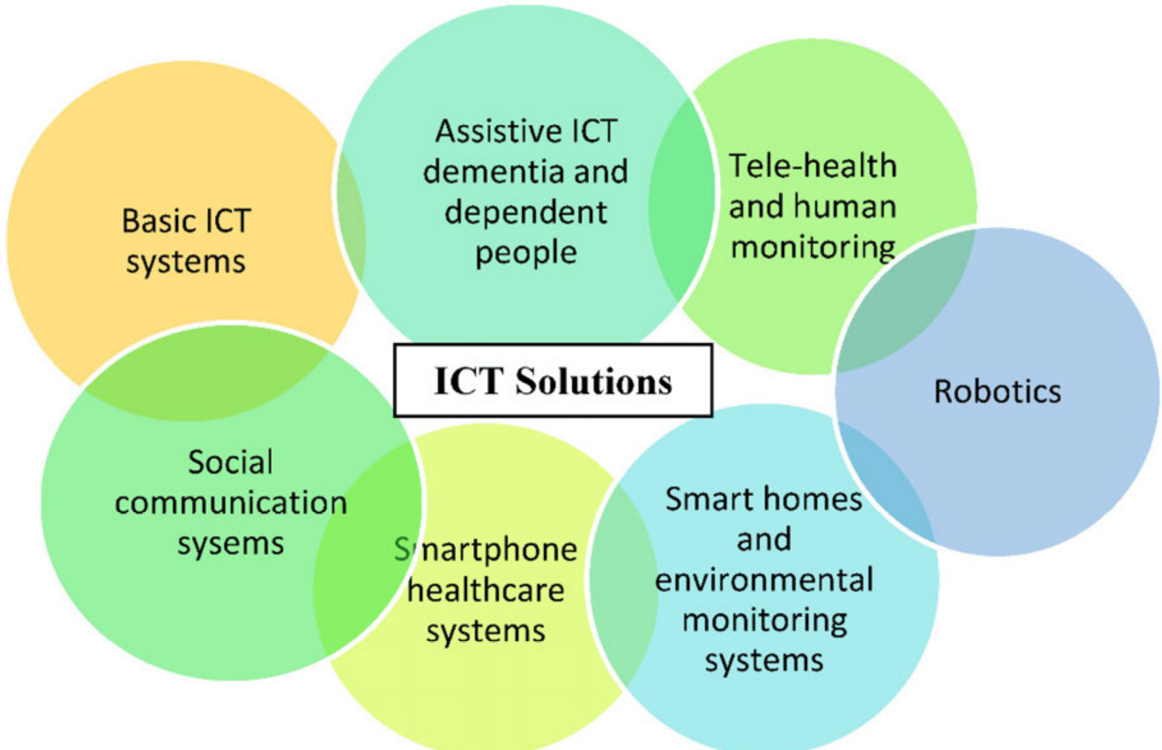

Figure 3. 4: Different categories of ICT solutions from the simplest technologies (e.g., basic ICT) to the more complex solutions (e.g., smart homes and telehealth).

Older people already use a wide range of ICT solutions in their daily lives. Such ICT solutions that are home-based, as televisions and microwave ovens, as well as computer-based technologies as internet and emails are considered Basic ICT Technologies. Basic ICT solutions have a positive impact on the QoL of older people living in their homes [36]. For example, internet-based technologies allow changes in older people's health behavior using different interventions as self-help programs and customized health-related data presentation through matching personal data to reachable interventions.

Social Communication Systems as mobile phones allow older people to stay in touch with their family members, caregivers, and clinicians or care providers. Social communication systems benefit older people living in their own environment by permitting social interaction using ICT solutions as video calling, thus decreasing isolation and depression levels in the older population as well as affecting older people's health and level of life satisfaction positively [37]. Despite the advantage of allowing remote social communication, it is feared that ICTs could elevate the feeling of loneliness of older people living in their own environment [38]. Video conferencing ICT systems are also considered social communication systems. An example of such a system is those supporting older people with chronic diseases. These systems provide access to older people's support around the clock and deliver a user-centered social care system interconnected to tele-medicine processes [39].

Smartphone Healthcare Systems give older people the opportunity to access their own health data and collaborate in their own healthcare process through accepting services that improve their health behavior. These systems provide older people with lifestyle guidance, fitness exercises, chronic disease management, as well as providing public health surveillance [40].

Smart Home Solutions and Environmental Monitoring Systems provide older people with a collection of procedures based on various devices and sensors displayed in their living environment. Such ICT solutions enable monitoring and management of older people's health using telehealth applications with the aim of improving their QoL and supporting their physical independence. Examples of smart home solutions and environmental monitoring systems can be fall detection systems, daily activity monitoring systems, and medical condition monitoring with vital data analysis. Such solutions address clinical syndromes through providing assurance and emergency assistance to the user and thus reducing caregivers' burden [41]. These systems allow the older user to be more involved in decision-making rather than being only the recipient of clinical decisions taken by clinicians [42].

Robotics is expected to play a major role in the healthcare of older people in the future [43]. Robots vary in the role they perform in helping the user to live actively and independently in their own environment. Robots fluctuate between service robots that support older people to perform daily activities and robots that act as social companions. Robotics is mainly applied in systems addressing mental health conditions since it has an impact on emotional, physiological, and social health [44].

Telehealth and Human Monitoring are addressed mainly to home hospice people and their caregivers. They provide different monitoring services such as functional services as sleep quality monitoring, safety services as detecting environmental hazards, physiological services as monitoring vital health parameters, and security services as alert alarms. Such monitoring technologies aim to increase the independence of the user through allowing real-time intervention just in time and provide him/her with acceptable support. Telehealth and human monitoring solutions enable the empowerment of the older user, the caregivers, and family members by permitting their involvement in the daily care process [45].

Assistive ICT for Dementia and Dependent People provides older people with chronic diseases such as dementia with more independence, safety, social communication, and an enhancement in activity performance. Thus, such solutions improve the QoL of older people living in their own environment. Older people using these systems are provided support in different areas of delivery of information. The provided support can be concerning their dementia symptoms, social interaction, health monitoring, and general safety. This type of ICT solution can increase its users' self-confidence and reduce levels of social isolation. These systems are proven to increase the feeling of safeness and reduce the feeling of fear and anxiety in older people with dementia [46].

3.2.3 Development of ICT Solutions

The main four themes that emerged throughout the development process of ICT solutions are: technology acceptance and readiness, novel patient monitoring and smart home technologies, intelligent algorithm and software engineering, and robotics technologies [47], as presented in ***Figure 3.5***.

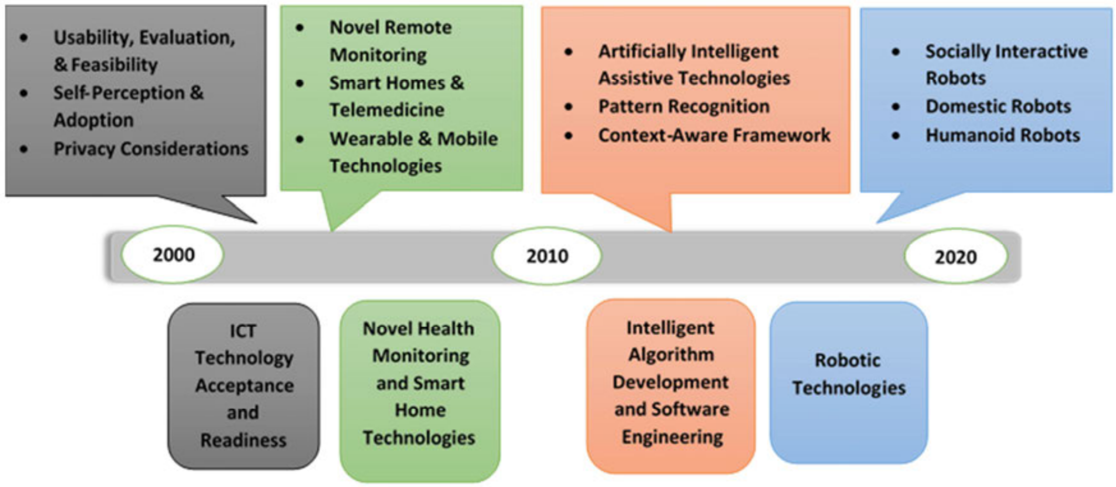

Figure 3. 5: A detailed view of the development process of ICT solutions with its different aspects.

ICT Technology Acceptance and Readiness involves studies that took place in the early 2000s and is considered to be the first era of technology research for the aging society. In this phase, researchers examined older people's acceptance of monitoring technologies using non-wearable sensors such as electronic health systems and smart home-based technologies using bed, motion, kitchen safety, and fall detection [31,32]. In addition to older people's acceptability, other studies investigated the usefulness, feasibility, and privacy of assistive tele-monitoring systems [33,34].

Novel Health Monitoring and Smart Home Technology are more sophisticated ICT systems that emerged after the year 2000. This type of system uses both wearable and non-wearable sensors. Such systems rely on interaction between sensors, mobile devices, cloud servers, and supervised machine learning approaches, novel protocols over SMS to allow communication between the older user and caregivers [35,36]. It was recognized that the blending of telemonitoring intervention with smart home technologies enhanced older people's skills in problem solving and self-efficiency in managing their medical conditions [37].

Intelligent Algorithm Development and Software Engineering became of great interest for research after 2010. This period is the second era of technology research for the aging society. In this phase, researchers explored the development of prototype systems, the establishment of new sensor-based smart home technologies, assistive robots’ development, and the conceptualization of new AI and machine learning solutions. This development in technology led researchers to the capability of developing new sophisticated AI algorithms and advanced context acquisition methods for advanced analyzation and automation of complex tasks [30]. An example of different intelligent algorithms is those involved in collecting data about the user’s environment and can predict potential problems for better decision-making (data mining algorithms). Examples of software development include the usage of context-aware middleware that can sense and respond to the user’s environment, the employment of pyroelectric sensors and infrared optoelectronic components with the aim of detecting electromagnetic radiation, and analyzing the collected data to monitor and manage user’s daily activity [38,39,40].

Robotics Technologies emerged around 2010. There are various robotic technologies that affect older people’s healthcare. They vary between advanced AI robotic technologies and simple assistive robotic activities [40,41]. Telepresence robots, companion robots, home automation and domestic assistive robots, rehabilitation and health monitoring robots, and reminder robots are examples of robotic systems that can be integrated with older people’s healthcare monitoring and management solutions. It is revealed that the development and multidisciplinary nature of robotic systems played an important role in providing better interaction with the aging population as well as contributing to therapeutic benefits [30].

Over the last decade, different ICT solutions concentrating on AI and machine learning or focusing on the development of context-aware and adaptive technology rapidly emerged. The systems concentrating on AI and machine learning and using sensors and smart home devices have the aim of investigating user perception, barriers, and novel system development. Other systems focusing on the development of a context-aware technology have the aim of being integrated into any environment, collecting information from different sensors and devices concerning temperature, geographic location, and user preference as well as delivering relevant data based on the older user’s unique set of variables. Sapci et al. [47] announced that the use of AI and sophisticated algorithms in the healthcare monitoring and management of older people can improve the accuracy and progress of the analytical techniques performed, thus making the monitoring and management process faster and more accurate.

3.2.4 Examples of ICT Solutions

ICT solutions can help older people to manage their chronic conditions on a day-to-day basis. The use of ICT solutions can handle age-related physical and cognitive impairments aiming to prolong the functional capacity of older people, delay their institutionalization, and increase their autonomy and participation in society.

Employment of ICT solutions for the early detection of chronic conditions enables older people's self-management of personal health records and use of a management tool that integrates different aspects of an older person's healthcare, including medical, social, and emotional issues. Older people with chronic conditions living in their own environment can be provided with adequate medical care and guaranteed health services through the use of efficient ICT networks [48].

Such ICT solutions involve continuous remote monitoring of older people for the management of different health conditions such as hypertension and blood pressure and improve the prediction of new health conditions, as well as older person's medication adherence.

ICT solutions permitting older person-centered care for diabetes mellitus involve blood glucose monitoring by telemonitoring systems, internet applications, and mobile devices. Such ICT solutions include smart algorithms to control blood glucose levels as decision-making processors.

ICT solutions allowing older person-centered care for chronic heart diseases provide the potential for health ambulatory monitoring and enable remote coordinated care by healthcare providers. The scope of advanced monitoring includes electronic weight scales, blood pressure (BP) meters, thermometers, as well as accelerometers for activity-monitoring and sleep-monitoring devices.

ICT solutions enabling older person-centered care for chronic obstructive pulmonary disease (COPD) include video or telephone links with healthcare providers either in real time or using store-and-forward technologies, internet-based telecommunication systems with healthcare providers, wired and wireless telemonitoring of physical parameters such as spirometry, respiratory rate, blood pressure, or oxygen saturation, pulmonary rehabilitation solutions with home-based video conferencing-supervised exercises and counselling, and telemonitoring of older people on home mechanical ventilation (HMV).

ICT solutions permitting older person-centered care for stroke mainly address physical care, consultation, and education. Such solutions provide monitoring services through integrating measurement devices, innovative interaction paradigms, customized motorial/cognitive neuro-rehabilitation treatments, continuous health status monitoring, cloud, and interoperable information systems.

ICT solutions allowing older person-centered care for cognitive impairment can support autonomous outdoor mobility, empowering participation in social events of older people with mild dementia. Such functionality is supported by assistive technology devices (ATDs), typically in the form of wearable devices which contain hardware and software that create a location-based service using global positioning system (GPS), cellular, and other signals.

Fall prevention intervention ICT solutions include fall detection and prevention ICT services to help older people live independently in their own environment by providing assistive support to clinical decisions. These ICT solutions concentrate on reducing fall risks and help older people to overcome them. Hamm et al. [49] parcelled fall prevention ICT solutions into four categories.

Pre-fall prevention intervention ICT solutions are ICT solutions targeting older people at risk of falling but who have not experienced any falling event yet. Such ICT solutions focus on the functional ability of the older user, supporting older people at risk of falling with services such as targeted physical activities and educational programs. These solutions have the aim of overcoming various intrinsic fall risk factors as balance, muscle strength and cognitive decline, and vision [8,50,51]. In this category of ICT solutions, gaming consoles as Wii and Xbox are deployed. For this reason, this category of fall prevention ICT solutions was excluded from the review.

Post-fall prevention intervention ICT solutions are ICT solutions focusing on older people who have previously experienced a fall by providing support to eliminate their risk of encountering future falls [47]. This category of fall prevention ICT solutions includes diagnostic assessment functions aiming to deliver re-active intervention to its users. These solutions include fall prediction solutions in this review.

Fall injury prevention intervention ICT solutions are ICT solutions that aim to enable assistive communication between older people and their care providers or clinicians. These systems include fall detection systems in this review. Fall injury prevention intervention ICT solutions target three main intervention types: activity monitoring, fall detection, and medical assistance. These solutions include fall detection solutions in this review.

Cross-fall prevention intervention ICT solutions are ICT solutions that support older people by delivering a blend of the previously mentioned fall interventions. This combination of different interventions has the aim of helping older people to manage their health conditions and to live independently in their own environment, using different ICT services that permit assistive collaboration between all older people, caregivers, and care providers. This category of ICT solutions includes fall prevention solutions in this review.

3.3 State of the Art and Research Results: ICT Healthcare Solutions for Assistive Living in the Aging Population

3.3.1 Research Question and Its Impact on the Analysis Process

This review sought to analyze health-related ICT solutions for the aging society. The performed analysis was based on our research question of whether the available health-related ICT solutions are effective, reliable, and acceptable in terms of encouraging active and independent living in older people, satisfying their needs, improving their QoL, as well as making it affordable [9]. There are several prototype and commercial ICT solutions for pervasive healthcare monitoring for older people with chronic diseases. It is observed that the focus categories include cognitive decline and mental health, fall detection, prediction and prevention, heart conditions, chronic obstructive pulmonary disease, diabetes, and strokes. ***Table 3.1*** lists ICT solutions covered in this systematic review under each medical condition. These technologies having the main aim of detecting changes in vital signs of the older person's health do not need to be embedded in the living environment [41,52].

Table 3. 1: Conditions/behaviors addressed by technologies (n = 63).

Medical condition and disability addressed	#papers	Study
Cognitive decline and mental health	16	[11,12,13,14,47,53,54,56,57,58,59,60,61,62,63, 64]
Stroke	6	[65,66,67,68,69,70]
Monitoring heart conditions	6	[15,71,72,73,74,75]
Chronic Obstructive Pulmonary Disease	5	[76,77,78,79,80]
Diabetes mellitus	6	[14,81,82,83,84,85]
Fall Detection	7	[26,86,87,88,89,90,91,92]
Fall prediction	9	[93,94,95,96,97,98,99,100,101]
Fall prevention	7	[102,103,104,105,106,107,108]
Total	**63**	

In a systematic review of the available ICT healthcare solutions for assistive living of older people between 2010 and 2014, ICT healthcare solutions were classified based on the major chronic illnesses of older people such as cognitive decline and mental health [55], monitoring heart conditions [73], obstructive pulmonary disease [80], fall prediction [91], and disease/disability prediction/health-related quality of life [109].

In another systematic review of the ICT healthcare solutions proposed between 1990 and 2018, the technologies were classified as either having the purpose of extending and sustaining older people's independent living in their own environment [12,14,15,59,62,65,66,68,69,76,78] or assisting and simplifying caregivers' activities [13,53,55,59,61,62,74,82]. It was stated that most of the discussed solutions were connected to specific chronic diseases such as Alzheimer disease and other dementias, diabetes mellitus, and stroke. With very few exceptions, most of the available ICT solutions were either in the research and development phase or early prototype phase.

3.3.2 Results of the Analysis

Our review determined that the analyzed studies focused on accepting available ICT technologies, developing new healthcare-monitoring and smart home technologies, enabling real-time channeling of data, and creating and integrating AI algorithms into ICT solutions. In this systematic review, the articles investigated included either randomized control trials (RCTs) or qualitative research of healthcare monitoring and management ICT solutions.

Table 3.2, **Table 3.3**, **Table 3.4**, **Table 3.5**, and **Table 3.6** cover ICT solutions for assistive living of older people with different medical conditions: cardiovascular disease, cognitive impairment and other dementias, COPD, diabetes, and stroke. In each table, the ICT solutions belong to different time frames and use different categories of ICT technologies or multicomponent ICT interventions.

Table 3. 2: ICT solutions for assistive living of older people with COPD.

Study	Project name	Year	Type & design	Objective	Findings	Limitations
Antoniades et al. [77]	*COMMONWELL Project: Early Intervention and Telehealth for COPD Patients - Milton Keynes.*	*2011*	*Pilot study. Telecare equipment (social alarm) and telehealth monitors in patients' homes. Telehealth readings and alarm calls at a joint call centre.*	*To improve the care for older people with COPD through an integrated telecare and telehealth service.*	*Developed and implemented integrated services supporting effective management of chronic diseases and addressed reduced mobility, vision, or hearing.*	*Not mentioned*
Pedone et al. [78]	*"SweetAge" monitoring system: Efficacy of multiparametric telemonitoring on respiratory outcomes in older people with COPD.*	*2013*	*RCT: A randomized controlled trial. Placed on the user's body. Consists of a wristband with sensors, a pulse-oximeter, a mobile phone.*	*Telemonitor user's oxygen saturation, heart rate, near-body temperature, and physical activity to evaluate the solutions efficiency in reducing hospitalization of older people with COPD.*	The study showed the ability to detect respiratory events timely using an automated wearable system that is easy to use by older people. It is concluded that the solution eliminated the risk of hospitalization by 33%.	Lower incidence of events, large confidence interval around the focus point.
Johnson et al. [79]	*KERSA Project*	*2013*	*KSERA Solution included a robot controller to control robot behaviour, a rule engine, and three databases. The system assures connection and coordination between the three components.*	Provide a framework to enable independent living of older people in smart homes through functional and social interaction with a robot.	The study fulfilled the older people's needs through providing the following services: health and behaviour monitoring using a mobile robot, environment monitoring using a robot integrated with smart household technology, provide audio and video communication services with caregivers.	Robot was expensive and lacks the ability to navigate in domestic environments.

Table 3.3: ICT solutions for assistive living of older people with Heart Conditions.

Study	Project name	Year	Type & design	Objective	Findings	Limitations
Wade et al. [71]	Telemonitoring With Case Management for Seniors with Heart Failure.	2011	RCT. A randomized clinical trial. Designed to allocate older people with high-risk HF using case management (THCM) versus case management (CM) alone.	Allow health management of older people with risk of heart failure by providing nurse case management services through telemonitoring.	Effective implementation of heart failure telemonitoring intervention.	The developed solution had no impact on lower levels of overall morbidity and mortality.
Muuraisking et al. [15]	V2me Project Evaluating the first steps in mobile friendship coaching.	2012	Pilot evaluation report - a prototype of V2me system	Develop a user-centred design addressing loneliness issues in older people through the use of an easy-to-use technology including touch screen devices.	The importance of constant older person involvement throughout development, implementation, training, and support while using of the developed system.	The final product was useful only to older people that have pronounced needs.
Hervas et al. [72]	Mobile monitoring and reasoning methods to prevent cardiovascular diseases.	2013	Use of mobile phones and sensors with Bluetooth communication. An integrated rule-based decision support solution.	To monitor risks of heart diseases in older people using mobile phones through developing an end-to-end software application.	Developed and evaluated an end-to-end solution for monitoring that can be used by patients, caregivers and doctors and uses smartphones.	The developed solution showed only 69% acceptance rate by older people.
Rifkin et al. [73]	A randomized, controlled clinical effectiveness trial of real-time, wireless blood pressure monitoring for older patients with kidney disease and hypertension.	2013	RCT. Telemonitoring device that pairs Bluetooth-enabled blood pressure cuff with an internet-based hub.	To monitor blood pressure of older people at home to improve blood pressure management of older people with kidney disease.	Greater sharing of data between older people at home and their clinicians using a low-cost wireless monitoring method. Improvement in blood pressure management.	The study had small sample size and was performed over a short duration.
Kantoch et al. [75]	Recognition of Sedentary Behaviour by Machine Learning Analysis of Wearable Sensors	2018	A Prototype of a designed shirt for activity recognition. Development of a method for gathering data from multimodal sensors and machine learning algorithms.	Obtain qualitative measurement older people's physical activity throughout developing a method for sedentary behaviour recognition.	High accuracy in detection of sedentary behaviour using smart shirts and machine learning techniques.	The detected set of activities is limited, advanced research is required.

Table 3.4: ICT solutions for assistive living of older people with Cognitive Impairment and other Dementias.

Study	Project name	Year	Type & design	Objective	Findings	Limitations
Mitseva et al. [110]	ISISEMD Project Intelligent System for Independent Living and Self-care of Seniors with Mild Cognitive Impairment or Mild Dementia.	2009	RCT: One-year randomized control trial in real-life conditions in four European countries. Pilot evaluation report.	Provide support for older people enabling them to live safely at home, supporting them with daily basic activities, permitting their social interaction with family members and caregivers to prevent their social isolation.	Delivered environmental monitoring and management services. Provided a mobile localization system. Assisted older people with reminder functions and communication and videoconferencing services.	Solution was in initial phases. System was not yet installed in the selected pilot sites.
Gellis et al. [58]	ALFRED Project Personal Interactive Assistant for Independent Living and Active Ageing.	2013	The ALFRED system consisted of three major sub-systems: - Client, on mobile device. - Server components. - A web portal.	-To empower older people to live independently. - To prevent age-related physical and cognitive impairments - To improve caring by offering direct access to vital signs for caregivers.	Provided older people with user-driven interaction assessment, personalized social inclusion, personalized and effective care, and prevention of physical and cognitive impairment.	Not mentioned
Hwang et al. [60]	Co-Designing Ambient Assisted Living (AAL) Environments: Unravelling the Situated Context of Informal Dementia Care.	2015	A user-centred design including a UCD model that studied users, designed a problem space, and built and evaluated prototypes.	- To identify and address the activities and situations for which older people needed AAL support. - To describe how older people can specify and obtain their needs.	Developed an activity-assistance AAL solution providing video demonstrations for older people and personalized the developed AAL system to older people's unique needs.	Sample size was small, included only females from one community-based support agency.
Alberdi et al. [64]	Smart home-based prediction of multi-domain symptoms related to Alzheimer's Disease.	2018	A regression analysis of smart home-based behaviour data. Longitudinal smart home data labelled with corresponding activity classes and extracted time series statistics containing 10 behavioural features.	-to develop tools for detecting earliest stages of age-related disorders like Alzheimer's Disease. -to evaluate the possibility of using unobtrusively collected activity-aware smart home behaviour data to detect multimodal symptoms to be impaired in AD.	-Created regression models to predict symptoms. -Built classification models to detect reliable absolute changes in the scores. -Used SmoteBOOST and wRACOG algorithms to overcome class imbalance. – Showed that activity-aware smart home data can predict mobility, cognition, and depression symptoms in the older person.	Early models of the system. Results require completion and improvement.

Table 3.5: ICT solutions for assistive living of older people with Diabetes mellitus

Study	*Project name*	*year*	*Type & design*	*Objective*	*Findings*	*Limitations*
Costa et al. [83]	*VirtualECare: Group Support in Collaborative Networks Organizations for Digital Homecare*	*2009*	*A study on the introduction of collaborative networks in the care of the older people as Group Decision Support Systems (GDSS).*	*To monitor and allow interaction between older people and caregivers through developing an intelligent multiagent system interconnecting to other computing systems running in different healthcare institutions, leisure centres, training facilities or shops.*	*Project in planning phase. Allow clinicians to achieve better analysis results from an older person's Electronically Clinical Profile (ECP) by the development of Group Decision Support Systems (GDSS) in the healthcare.*	*Incomplete system. Multiple unrecognised data sources as unreachable sensors, incomplete user's Electronic Clinical Profile.*
Jara et al. [14]	*Movital: An internet of things–based personal device for diabetes therapy management in ambient assisted living (AAL)*	*2011*	*Movital includes the module SkyeModule M2 from SkyeTek for contactless identification to identify patients, and load patient health profile, and the module Jennic JN5139 for Wireless Sensor Networks (WSN) communications.*	*It provided a diabetic older person with an electronic personal device that stores blood glucose readings and gave advice about the next meal and insulin injection.*	*Supported an older people's profile management service implementing personal RFID cards and provided global connectivity between older person's personal device and care providers or clinicians, and developed a desktop application to manage user's personal health cards, glycaemic index information system, and user's web portal.*	*Not mentioned*
Salvo et al. [85]	*SWAN-iCare (smart wearable and autonomous negative pressure device for wound monitoring and therapy).*	*2017*	*A study on monitoring diabetic foot and venous leg ulcers using temperature and pH sensors*	*To allow continuous monitoring of foot ulcers associated with diabetes.*	*PH sensor showed to be suitable for pH measurement in laboratory trials.*	*Sensors required clinical validation.*

Table 3.6: ICT solutions for assistive living of older adults that encountered a stroke.

Study	*Project name*	*Year*	*Type & design*	*Objective*	*Findings*	Limitations
Pastorino et al. [67]	CogWatch project: Preliminary Evaluation of Personal Healthcare System Prototype for Cognitive eRehabilitation in a living Assistance Domain.	*2014*	*Prototype phase.* *Designed to promote independence in activities of daily living for older people with apraxia. Included a Kinect and a set of sensors.*	*To collect data for executed tasks and movements of an older person to permit recognition of any action errors.*	Showed 99% success in storing data correctly in terms video records, tracking records, and streaming records. The ability to analyse the behaviour of external devices. Analysis of the behaviour of the external devices, i.e. Kinect, smart watch, and sensored tools.	System should be more flexible for use by older people, who required an improvement in the user interface.
Oliver et al. [70]	*Ambient Intelligence Environment for Home Cognitive Telerehabilitation.*	*2018*	*A study that uses smart sensors, actuators, and a headset to implement a Fuzzy inference system with an attempt to take place of a clinician.*	*To analyse the movement of upper extremities of an older person by capturing his/her body shape using a Kinect depth camera.*	Provided both older people and their care providers with greater power and control.	Sample size was limited. Faced older people's fear from the increasing dependency of rehabilitation on machine automation.

An in-depth analysis is carried out regarding the sensing technologies, smart technologies, and novel methods used in ambient assistive living (AAL) of older people with chronic diseases. Other aspects discussed in the analysis are the user interface, the older user, as well as the maturity level of the available ICT technologies. Finally, this paper reviews the older people's acceptance and satisfaction of the discussed ICT technologies.

Table 3.2 provides examples of different categories of ICT solutions for older people with COPD. We selected a few articles discussing ICT solutions for older people with COPD as in Antoniades et al. [77]. The COMMONWELL project [76] allowed the combination of social care and healthcare for older people with COPD through developing an integrated e-care solution. Both client and server web services were implemented following a common interface. The services implemented provided an interface to exchange information such as username, ID, gender, social security number, call reason, user's current medication, diseases, and allergies, etc. The proposed ICT solution providing telecare services for COPD patients showed positive effects on the older users' mental health. The user's feeling of security increased, whereas hospital admissions decreased throughout the study duration. The KERSA project [79], on the other hand, used sensors and devices, speech recognition and generation methods, robotic services, person-aware navigation techniques, an audio and video communication service, and eye contact and emotional monitoring to assist older people with COPD in living independently. It integrated smart home technology with assistive robotic services to serve older people's needs.

Table 3.3 provides several ICT solutions for older people with heart conditions that use different approaches. The V2me project [15] developed an ICT solution for older people with heart conditions. V2me (Virtual coach reaches out to me) was an Ambient Assisted Living Joint Program (AAL JP) project that involved social network activities to enhance the quality of life of older people. The V2me project idea came up within another AAL JP project called A2E2 (Adaptive ambient empowerment of older people). The A2E2 project included a virtual-coach-assisted system that supports older people having diabetes type II and cardiovascular diseases with their lifestyle management. The developed system was implemented on an all-in-one PC having a touchscreen located in the older person's home. The V2me system aimed to tackle aspects of the social behavior of older people, mainly loneliness. It developed a user-centered designed system and implemented it on touchscreen devices to diminish loneliness in older people. Hervas et al. [72], on the other hand, developed an end-to-end software application that monitors the risk of heart diseases in older people, integrating a smartphone, sensors, high response speed, and rule-based decision support services in one system. This system benefits all the older persons, caregivers, and care providers. Kantoch et al. [75] developed a cardiovascular risk-based system that automatically recognizes any inactive behavior related to the heart and quantitatively measures older people's physical activity. The system collected data from multimodal sensors, used a machine learning algorithm for activity recognition, and applied an experimental protocol for validation.

Table 3.4 consists of a group of selected ICT solutions that made a difference in the assistance of older people with cognitive impairment and other dementias as in existing works [44,56]. The ISISEMD project [110] provided a services package that allowed caregivers to remotely support older people whilst tolerating ethical rules and permitted family members to communicate and support older people with cognitive impairment and other dementias in their independent living. This system deployed environmental monitoring and control, a mobile localization system, a tele-care service, reminder functions and brain games, and communication and videoconferencing. Alberdi et al. [64] developed a smart home-based system to detect multimodal symptoms related to Alzheimer's disease. This system used sensors, devices, environmental sensors, and machine learning software to evaluate mood and cognition. The developed system measured the level of an older person's mobility using the Arm Curl test. It detected changes in the older person's cognitive and mobility skills. The model discussed is an early model. The need for collecting more data and integrating machine learning algorithms is intended as future work with the purpose of building accurate prediction models and adjusting to imbalanced detection problems prior to the system's implementation in the real world.

Table 3.5 provides selected ICT solutions for older people with diabetes mellitus as in existing works [81]. Earle et al. [84] developed a mobile telemonitoring system for older people with diabetes; this system has the potential for delivering intensified care to improve blood pressure control, and its use may be associated with reduced exposure to hyperglycemia. Blood pressure readings were transmitted wirelessly via sensors in the mobile phone to the central server. This system allowed real-time transmission of data between users and care providers using a web-based application delivering management services. Salvo et al. [84] developed a smart wearable and autonomous negative pressure device that benefits from temperature sensors and pH sensors to monitor and manage chronic ulcers over time. In laboratory settings, the developed system proved to be suitable for pH measurement but still needs clinical validation.

Table 3.6 provides selected ICT approaches for the assistance of older people encountering strokes. Pastorino et al. [67] developed a CogWatch framework to evaluate a platform for the personal rehabilitation of older people that encountered a stroke. This framework consisted of the monitoring device, CogWatch, the Client Sub-system (CCS), and the CogWatch Professional Interface (CPI). The developed system was designed to monitor user's movement and task execution data and recognise the presence of any action error. This monitoring system used a set of sensors, cameras, a kinetic device, servers, web application, and a user interface. Oliver et al. [70] developed an ambient intelligence environment for the home cognitive telerehabilitation of older people. This system aimed to provide users with more self-reliance, using a headset for emotional detection, a Kinect version 2, a Glove vibrotactile sensor, servers, and web-based services with client applications.

Most of the ICT solutions used for the different chronic diseases use web or mobile applications that need to be more interactive and user friendly. Several solutions consider speech recognition to process user input. A large group of the solutions considered non-invasive sensors (in terms of privacy and personal space) which are creditable. Almost all the solutions consider the older person as the user and consider a collaboration between the older person, caregiver, and, in some cases, the care providers. It is noticeable that almost all the ICT solutions discussed are at the R&D or prototype level. Most of the solutions did not report technology acceptance or user satisfaction. The solutions ranged between health monitoring and management and activity monitoring with the inclusion of an alert system or reminder service for users.

Table 3.7 provides fall prediction ICT solutions for assistive living of older people. Fall prediction interventions [93,94,99,100,101] delivered functional, cognitive, and environmental assessment to the user. Majumder et al. [96] developed a smart phone-based fall assessment system by integrating sensor data from a smartphone and a smart shoe. The developed system collected the user's data in any environment using a smart shoe containing four pressure sensors with a Wi-Fi communication module. This system monitored abnormal gait patterns while performing ADLs. Staranowicz et al. [97] proposed a mobile Kinect-based gait-monitoring system for fall prediction that used an autonomous robot which monitored the walking patterns of older people during their ADLs at home and recognized functional decline.

Table 3. 7: ICT solutions for fall prediction systems for assistive living of older people.

Study	Project name	Year	Type & design	Objective	Findings	Limitations
Ferreira et al. [95]	A Pilot Study Testing a Fall Prevention Intervention of Older Adults.	2012	A descriptive study on monitoring healthy older wearing sensors people while performing different movements. System included five wireless placed on the user's wrists, ankles, and chest.	To continually monitor and display older people's movement and send real-time alarms for fall prevention. To use a standardized script to direct an older person's movement with attached on-body sensors.	The system achieved high accuracy levels where sensor data output always matched video output.	Small sample size. Lacked accuracy and acceptance of hospitalized older people.
Majumder et al. [96]	smart Prediction: A Real-time Smartphone-based Fall Risk Prediction and Prevention System.	2013	A study that integrated sensor data of smartphones and a smart shoe to predict falls. Smart shoe is designed to include four pressure sensors with Wi-Fi connection to collect data in any environment.	To recognise walking patterns and generate an alert message to the user in case of encountering high risk gait patterns to save them from near falls.	Showed a 97.2% accuracy in real-time detection of gait abnormalities in users.	Need to be tested on real older people with chronic gait problems.
Staranowicz et al. [97]	A Mobile Kinect-based Gait-Monitoring System for Fall Prediction.	2013	RCT. A randomized control trial to monitor human gait during daily-life activities through deploying a high-accuracy motion-capture system. It consists of Kinect and a robotic platform.	To allow collection of fall-prediction gait parameters without the use of on body sensors with unlimited capture volume.	The system included a depth camera mounted on a robot that enabled high accuracy to be revealed.	Gait parameters and analysis need to be expanded. A comparison between fall predictions is required from clinicians.

Most of the proposed fall prediction systems did not provide the user with an interactive interface, which implies their static nature. Majumder et al. [96] and Almer et al. [98] developed static applications that used smartphone sensors to collect fall relative data from older people's behavior while living in their own environment.

Table 3.8 presented fall detection ICT solutions for assistive living of older people. Fall detection systems included solutions [25,87,88,89,90] that focused on eliminating fall injuries. Abbate et al. [88] proposed a fall detection system that integrated an artificial neural network and feature extraction machine learning methods to monitor the older person's movement behavior and produce emergency alerts after a fall was detected. Wang et al. [92] proposed a refined fall detection system that used on-body smart sensors operating in the older person's living environment to monitor their movement behavior. This system focused on the common changes in the user's movement behavior accompanying an accidental fall. These include changes in impact magnitude, trunk angle, and after-event heart rate. It collected and analyzed data from an accelerometer, smart sensors, and a cardiotachometer to accurately distinguish between older people's ADLs and fall-related behaviors.

Table 3.8: ICT solutions for fall detection systems for assistive living of older people.

Study	Project name	Year	Type & design	Objective	Findings	Limitations
Abbate et al. [88]	A Smartphone-base fall detection system	2012	A prototype of the system was tested on a small sample group. Used a small external sensing unit to eliminate the intrusiveness of the system.	Monitor older people's movement patterns, detect a fall, and send automatic alerts for caregivers to provide support.	Proved that the recognition of fall-like activities of daily living (ADL) can significantly reduce the number of false alarms depending on peculiar features of the acceleration patterns of the user.	The small size of the sample group limited drawing conclusions with high confidence.
Abbate et al. [89]	MIMS: A Minimally Invasive Monitoring Sensor Platform	2012	A platform for the development of a health monitoring system based on older people's needs. It included a Virtual hub and a gateway. A gateway for communication of captured data and enables coordination of signal processing and fusion of sensor data.	To predict emergency events through analysing the physiological signal data of the user. To allow communication of collected data, signal processing, and fusion of sensor data through using a gateway.	Optimized the quality of sensor data using a monitoring application that joined data acquisition and processing.	Long Installation time was required, coverage capability was limited, and included privacy violations.
Terroso et al. [90]	A Wearable System for Fall Detection	2013	A study on the use of a system built up from a wearable sensor, a smartphone, and a website.	Provide higher autonomy to the older population, allowing for a more active lifestyle.	Sent an alert using the smartphone to family members or when a fall is detected. In case of unconsciousness, the alert message was sent after a pre-defined time interval.	Carrying the smartphone and having access to mobile network.
Cabestany et al. [91]	FATE Project	2013	Pilots are organized in three different countries under one year, involving 175 users. Includes accelerometers and gyroscopes for reliable fall detection.	To organize a big pilot on automatic fall detection of older people living at home.	An accurate, real-time detection of falls in older people.	Not mentioned

Most of the presented fall detection solutions developed data filtering methods to distinguish fall-related behavior from ADLs. These systems function by gathering older person's movement data profiles, detect a fall and send automated alerts to caregivers and/or care providers, and filter false detection.

There appear to be limited fall detection solutions deployed on game console platforms. Both Abbate et al. [88] and Abbate et al. [89] developed on-body fall detection solutions. These solutions were implemented on a smartphone that needed to be worn by the older user as a wearable device. Most of the presented fall detection ICT solutions were set up from three fundamental components, i.e., included a device with embedded wearable sensors to collect physiological data from the older user, a filtering method to distinguish fall related events from ADLs, and a form of communication in case of emergency [111].

To detect a fall, a range of information sources need to be exploited. The location of the sensor on the older user or in the living environment is important for the fall detection process. Terroso et al. [90] developed a fall detection system that collected users' movement data using a wearable accelerometer and sent it to the smartphone and server for further analysis. The accelerometer sensor communicated to a smartphone application through Bluetooth to perform the analysis. The geographical location of the user was logged using a smartphone GPS sensor. The system delivered messages to the caregivers in case of emergencies. In other works (for example, Kepski et al. [86]), context was the main information source used. Data were conservatively collected from older people, and this is considered less intrusive than approaches with sensors placed on the user's body. This approach used a Kinect to detect falls of older people in their living environment. This system performed 3D tracking of the users but had some limitations such as limited spatial coverage and inability to monitor user's movement while walking.

Table 3.9 provides cross-intervention fall prevention ICT projects for assistive living of older people with chronic diseases. Shi et al. [102] developed a fall prevention system for the assessment of fall risks using a smartphone application. This system detected falls after their occurrence using clinical tests for the purpose of preventing fall-related injuries. Chou et al. [103] presented another type of fall prevention system. This system detected changes in the position of the user from lying to sitting while getting out of bed and then sent alarm signals when a risk of falling was detected, allowing immediate support by caregivers.

Table 3.9: ICT solutions for cross fall prevention systems for assistive living of older people.

Study	Project name	Year	Type & design	Objective	Findings	Limitations
Barban [105]	ModulAAR	2014	Study protocol. A pre- and post-assessment, longitudinal, and quasi-experimental cohort study. Study duration was 18 months and included 2 pre-assessments in 7 different sites in Austria.	Use of ICT to help older people enhance their QoL through health improvement and independent living if possible.	Provided environmental monitoring and control, Individual and health monitoring, a fall detection system with localization and emergency services, reminder functions, social interaction application, communication, and video conferencing,	Not mentioned
I DON'T FALL [106]	I DON'T FALL Project	2015	A Medical evaluation report and framework. A randomized control trial consisting of four arms. It detects falls and prevent injuries and tested by over 500 older patients across Europe for 9 months.	Enable care providers to monitor older people more efficiently and cost effectively and equip potential fallers with appropriate devices.	key innovations: a robotic rollator – the i-walker. Delivered a fall detection system providing the older people with fall prevention services as warnings, and technical assistance for physical training through tele-rehabilitation.	Not mentioned
ReAAL [107]	I STOP FALLS Project	2015	RCT, 153 community-dwelling participants performed the program for 16 weeks.	Reduce older people's risk of falling.	The developed program reduced user's physiological fall risks. It showed an improvement in postural sway, stepping reaction, and executive function.	Small improvement in older people's QoL was detected.
Liu et al. [109]	universAAL Project (make it ReAAL)	2016	An evaluation report of a qualitative longitudinal study involving pre- and post-interviews with older people moving to new assisted living homes.	The development of a single communication platform for digital purposes targeting psychologically less independent older people.	Provided an emergency call system, an environmental control system, and a social communication system.	Difficulties and delays in setting up application-level service provision.

The previously mentioned cross-fall prevention intervention systems utilize a full range of techniques that correlate with both fall prediction and detection with the target of assessing, detecting, and responding to fall risks. In this systematic review, we do believe that the wider the range of weaknesses, risks, disabilities, and diseases monitored in an older person, the more results we obtain out of the cross-fall prevention intervention. Different qualitative fall prevention approaches were developed throughout Europe. I-DON'T FALL [106] is a project that analyzed a fall prevention system for older people with cognitive impairment. This system showed positive effects on older people's quality of life through reducing their fear of falling and the risk of falling and enhanced the older people's mobility. I STOP-FALLS [107] is another project that focused on fall detection and fall-related factors that promised to provide a fall prevention system with a wide range of services including a fall risk assessment and prediction system and a personal health advisor. The large international AAL project ReAAL [108] encompassed older people residing in newly developed assisted living homes equipped with AAL systems. The developed solution developed an emergency calling service, a social communication service, and an environmental control service through developing 32 applications in different pilot sites with the aim of including a very large number of older people from different countries in Europe. These applications collected data from users as minimal datasets, surveys, real-time tests, issue reporting by user, etc. This solution was not tested by older people and faced many challenges on an organizational level, deployment level, as well as user recruitment and consent level.

3.4 Discussion

In this systematic review, 63 articles were selected according to their relevance to the research question and ICT solutions focusing on the biomedical perspective of aging. Then, an analysis of the objectives, impacts, and role of the presented ICT solutions in monitoring and managing the chronic diseases, ADLs, and falls and near-falls was performed. The analysis performed has sought answers of whether the presented solutions were effective, reliable, and acceptable by the aging population. Most of the selected papers discuss ICT solutions connected to cognitive impairment and other dementias (16×) and fall interventions (24×), while other chronic diseases were represented by 5 to 7 articles each (Table 1).

In recent years, there has been a high demand for monitoring older people with any kind of dementia [11,55,59]. AAL technologies [57] as well as smart home systems [55,66] have been extensively proposed as effective ICT solutions for older people with dementia and their caregivers. With the objective of a more independent life, these solutions monitor the older people using passive and active IR motion sensors [59] or video monitoring systems [11,79] depending on the level of accuracy required.

Diverse presented research papers that discussed and evaluated the use of ICT solutions for AAL of older people. A group of papers discussed the older people's ability and acceptance of using tablets and touchscreen devices [15,60,62,68]. Hwang et al.

[60] explained that the developed ICT solutions need to be flexible, customizable, and have the feature of Do It Yourself (DIY) to enhance the older people's healthcare, experiences, and relationships while living in their own environment. Muuraiskangas et al. [15] emphasized the importance and the necessity of the user's involvement throughout the development, implementation, and testing phases of the developed ICT solutions to enable a smooth transfer of the ICT solutions from virtual settings to the real world.

Currently, the use of multicomponent interventions and smartphones is becoming a trend. It is reported that older people living in their own environment have the ability of using different ICT solutions such as smartphones and wearable devices [81]. Web or mobile applications are generally used in most of the discussed ICT solutions for speech recognition. It is observed that non-invasive sensors and smart capabilities are becoming a trend in new ICT solutions.

Almost all ICT solutions consider the older person as the user. In general, the older person, caregivers, and/or healthcare providers are intended to use the system in collaboration. The state of development of ICT solutions in most of the publications is either R&D or prototype phase. This incompleteness in the development process of the solution is predictable considering the nature of the problem, where almost all discussed solutions did not announce older people's acceptance and satisfaction in the developed ICT solutions. This problem is caused due to the older person's distrust in using the developed ICT solutions in their daily life, as mentioned in many research papers [17,67,72,90].

Almost all ICT solutions as the ones connected to fall prevention focused on deploying machine learning techniques and advancing AI algorithms to improve fall detection solutions' levels of accuracy, specificity, and sensitivity. Very limited effort was applied on the design and user interface of the developed ICT solutions. Most of the deployed applications were static, having the main role of detecting falls as they occur. The presence of interactive applications to interact with the users to reduce fall risks was not observed in most developed ICT solutions.

It is important to mention that older people need to be willing to wear the device in the first place. The user may consider solutions with built-in accelerometers and gyroscopes, as the one developed by Abbate et al. [89], but they are intrusive and expensive. Alternatively, there are other presented solutions that used camera sensors [86], pressure sensors, and audio sensors or brand-specific sensors as Microsoft Kinect. Kepski et al. [86] developed a fall detection system that reused a Kinect to collect older people's data while living in their own environment.

Almost all the presented ICT solutions used multimodal interaction to collect data from the user, control the system, and allow interaction between the users, caregivers, and/or care providers using interaction devices. Most approaches used non-interactive interfaces, while only some systems presented [88,89] used both non-interactive interfaces and touchscreen gestures.

As for fall-related ICT solutions, the fall detection and prediction literature appear to be overloaded with solutions that monitor user's activity, detected falls, and sent alerts. Nevertheless, there are some challenges associated with these solutions and their use in practice. There is a need for more accurate detection of falls with an advanced ability to distinguish fall events from ADLs. Another challenge is preserving the user's privacy. One way of preserving the user's privacy is the use of camera sensors instead of wearable sensors.

In almost all existing ICT solutions, artificial intelligence employment was reported. This means that any increase in the quantity of the user's collected data will have a positive impact on the developed ICT solution.

The smart capabilities, the non-intrusiveness, and the possibility of interaction between older people, caregivers, and/or healthcare providers, in the discussed ICT solutions, highlight the potential that these solutions have in enhancing the quality of life of older people with chronic diseases and maintaining their health and wellbeing [17].

Finally, it should be noted that the findings of this review cannot be generalized to the heterogenous aging population. Thus, depending on the heterogeneity of an aging population, different approaches and technologies are required based on the diverse needs of the specified aging population. This indicates a key limitation facing the wide adoption of technology in heterogeneous aging populations. Our foundation in addressing this limitation would be the development of smart gateways or interfaces to be adaptive, learn from the user, and address each user's unique biomedical and chronic needs.

3.5 Conclusions

Based on the literature review performed, the currently available ICT solutions considered the subtleties of the disease instead of the wider context, i.e., the chronic disease in correlation with the older person's unique health and capabilities profile and the unique characteristics of the lived-in environment. Frequently, many of the available ICT solutions are used along the chronic diseases and disabilities rather than managing the healthcare and abilities profile of the older person as a whole [17].

After analyzing the various healthcare monitoring and management ICT solutions, different research gaps were identified and stated here. The existing ICT solutions do not tackle the fusion process of data captured using wearables from both contextual and physiological sensors. New data sources need to be identified and more comprehensiveness in the developed solutions is required. This implies the need for future research on more efficient and sophisticated means of collecting, managing, and analyzing data and delivering medical information to caregivers and care providers, helping to drive data-informed health care decisions. More insight into the use of data analytics and health informatics tools as machine learning, database management, cloud computing, predictive analytics, and data visualization is required in future research. The developed ICT solutions need user-friendly interfaces and feedback techniques for more engagement and empowerment of older people in their own healthcare management process. There is a need to address user interface effectiveness, efficiency, and satisfaction by older people in future research. Although healthcare providers or clinician's interactions were included in some of the developed ICT solutions, there is a need for interactive, comprehensive, and powerful web interfaces to permit effective visualization of older people's health data and provide helpful support [112].

Therefore, deploying comprehensive, interactive, and effective ICT in areas of assisted healthcare enables older people living in their own environment to perform unsupervised contributions with remote monitoring by healthcare providers, but still there is no evidence of the effect of ICT solutions on older people's health outcomes.

Identifying the challenges facing the current healthcare monitoring and management solutions for older people makes the direction of future research more evident. In this regard, the presence, and the involvement of ICT solutions in assisting older people with daily activities in their daily life is increasing. Nevertheless, older people are unwilling to utilize ICT solutions with wearable sensors due to privacy and security concerns [66]. The mental exhaustion of using wearable technologies is another reason for the unacceptability of these technologies by older people. There is thus a need for a balance in means of accessing and/or sharing the users' data while maintaining their privacy and security by controlling older person's data accessibility, recognition of potential attacks by security and privacy providers, and ensuring that wireless networks and messaging systems are secured. The developed ICT solutions need to be more personalized to the user's requirements, more pervasive, and multifunctional [113,114].

This leads to the identification of user-oriented requirements of smart ICT solutions. They need to be designed and implemented targeting user's acceptance and satisfaction of the developed solutions. To fulfil the need of helping older people manage their chronic diseases and disabilities while living in their own environment, a set of requirements must be addressed by the ICT solutions [115]. Older people are not comfortable with the technology being provided due to its unusefulness to them or due to the increase in their feeling of being stigmatized and disabled. ICT solutions should not be obstructive, thus leading to disuse by the user. The user's privacy and security while using the solution need to be boldly recognized and understood by the user. The ICT solution must be affordable to be owned by older people. Finally, and most importantly, the developed ICT solutions need to support older people in staying in their own environment as well as moving in various environments.

Based on the reviewed literature, one can conclude that the topics of disability prediction, health related and independent QoL, and fall prevention are not adequately covered in the developed ICT solutions. It is concluded that the developed ICT solutions are not flexible, adaptive, or user oriented. They do not provide assistive support for any health or disability predictions, and none of the developed ICT solutions can be considered to be low-cost solutions [17,109,112].

References

[1] A. Peine, A. Faulkner, B. Jæger, and E. Moors, "Science, technology and the 'grand challenge' of ageing—Understanding the socio-material constitution of later life," Technol. Forecast. Soc. Chang., vol. 93, pp. 1–9, 2015.

[2] W.R. Hazzard, "Principles of Geriatric Medicine and Gerontology, 3rd ed.;" McGraw-Hill Companies, New York, NY, USA, 1996.

[3] J.E. Morley, "The top 10 hot topics in aging," J. Gerontol. A, vol. 59, pp. M24–M33, 2004.

[4] World Health Organization, "Falls," 2018. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/falls. [Accessed: 25 October 2020].

[5] P. Couturier, "Place de l'actimétrie dans la gestion médicale du sujet âgé fragile," Gérontologie Soc., vol. 2, pp. 13–23, 2005.

[6] A.M. Herghelegiu, G.I. Prada, A.M. Marin, and R.M. Nacu, "Risk factors and prevention strategies for falls in the elderly," in Proceedings of the 2015 E-Health and Bioengineering Conference (EHB), Iasi, Romania, 19–21 November 2015, pp. 1–4.

[7] M.E. Tinetti, M. Speechley, and S.F. Ginter, "Risk Factors for Falls among Elderly Persons Living in the Community," N. Engl. J. Med., vol. 319, pp. 1701–1707, 1988.

[8] M. Montero-Odasso, J. Verghese, O. Beauchet, and J.M. Hausdorff, "Gait and Cognition: A Complementary Approach to Understanding Brain Function and the Risk of Falling," J. Am. Geriatr. Soc., vol. 60, pp. 2127–2136, 2012.

[9] D. Pal, S. Funilkul, N. Charoenkitkarn, and P. Kanthamanon, "Internet-of-Things and Smart Homes for Elderly Healthcare: An End User Perspective," IEEE Access, vol. 6, pp. 10483–10496, 2018.

[10] L. Magnusson and E. Hanson, "Supporting frail older people and their family carers at home using information and communication technology: Cost analysis," J. Adv. Nurs., vol. 51, pp. 645–657, 2005.

[11] G. Sacco, V. Joumier, N. Darmon, A. Dechamps, A. Derreumaux, J.H. Lee, J. Piano, N. Bordone, A. Konig, B. Teboul, et al., "Detection of activities of daily living impairment in Alzheimer's disease and mild cognitive impairment using information and communication technology," Clin. Interv. Aging, vol. 7, pp. 539–549, 2012.

[12] F. Rudzicz, R. Wang, M. Begum, and A. Mihailidis, "Speech interaction with personal assistive robots supporting aging at home for individuals with Alzheimer's disease," ACM Trans. Access. Comput., vol. 6, 2015.

[13] F. Cavallo, M. Acquilano, and M. Arvati, "An ambient assisted living approach in designing domiciliary services combined with innovative technologies for patients with Alzheimer's disease: A case study," Am. J. Alzheimer Dis. Other Dement., vol. 30, pp. 69–77, 2015.

[14] A.J. Jara, M.A. Zamora, and A.F.G. Skarmeta, "An internet of things–based personal device for diabetes therapy management in ambient assisted living (AAL)," Pervasive Ubiquitous Comput., vol. 15, pp. 431–440, 2011.

[15] S.T. Muuraiskangas, A.K. Leist, A. Braun, K. Klauß, P.H. Roelofsma, R. Wichert, P. Klein, and D. Ferring, "V2me: Evaluating the first steps in mobile friendship coaching," J. Ambient. Intell. Smart Environ., vol. 4, pp. 517–534, 2012.

[16] World Health Organization, "The Top Ten Causes of Death," 2019. [Online]. Available: https://www.who.int/news-room/fact-sheets/detail/the-top-10-causes-of-death. [Accessed: 29 January 2021].

[17] P. Maresova, O. Krejcar, S. Barakovic, J.H. Barakovic, P. Lameski, E. Zdravevski, I. Chorbev, and V. Trajkovik, "Health–related ICT solutions of smart environments for the elderly–systematic review," IEEE Access, vol. 8, pp. 54574–54600, 2020.

[18] A. Mihailidis, A. Cockburn, C. Longley, and J. Boger, "The Acceptability of Home Monitoring Technology Among Community-Dwelling Older Adults and Baby Boomers," Assist. Technol., vol. 20, pp. 1–12, 2008.

[19] M.K. Swartz, "The PRISMA Statement: A Guideline for Systematic Reviews and Meta-Analyses," J. Pediatr. Health Care, vol. 25, pp. 1–2, 2011.

[20] S. Waffenschmidt, M. Knelangen, W. Sieben, S. Bühn, and D. Pieper, "Single screening versus conventional double screening for study selection in systematic reviews: A methodological systematic review," BMC Med. Res. Methodol., vol. 19, pp. 1–9, 2019.

[21] M.T. Mardini, Y. Iraqi, and N. Agoulmine, "A survey of healthcare monitoring

systems for chronically ill patients and the elderly," J. Med. Syst., vol. 43, pp. 50, 2019.

[22] G. Acampora, D.J. Cook, P. Rashidi, and A.V. Vasilakos, "A survey on ambient intelligence in health care," Proc. IEEE, vol. 101, pp. 2470–2494, 2013.

[23] K. Chaccour, R. Darazi, A.H. El Hassani, and E. Andres, "From Fall Detection to Fall Prevention: A Generic Classification of Fall-Related Systems," IEEE Sens. J., vol. 17, pp. 812–822, 2016.

[24] K.M. Culhane, M. O'Connor, D. Lyons, and G.M. Lyons, "Accelerometers in rehabilitation medicine for older adults," Age Ageing, vol. 34, pp. 556–560, 2005.

[25] Y.S. Delahoz and M.A. Labrador, "Survey on Fall Detection and Fall Prevention Using Wearable and External Sensors," Sensors, vol. 14, pp. 19806–19842, 2014.

[26] W. Tao, T. Liu, R. Zheng, and H. Feng, "Gait Analysis Using Wearable Sensors," Sensors, vol. 12, pp. 2255–2283, 2012.

[27] R.A. Kenny, C.N. Scanaill, and M. McGrath, "Falls Prevention in the Home: Challenges for New Technologies," in Intelligent Technologies for Bridging the Grey Digital Divide, IGI Global: Hershey, PA, USA, 2011, pp. 46–64.

[28] A. Zamkah, T.K. Hui, S.C. Andrews, N. Dey, F. Shi, and R.S. Sherratt, "Identification of Suitable Biomarkers for Stress and Emotion Detection for Future Personal Affective Wearable Sensors," Biosensors, vol. 10, pp. 40, 2020.

[29] G.E. Sakr, I.H. Elhajj, M.K. Joujou, S. Abboud, and H.H. Abu-Saad, "Portable Wireless Device for Automated Agitation Detection," in Cross-Cultural Training and Teamwork in Healthcare, IGI Global: Hershey, PA, USA, 2013, pp. 236–255.

[30] P. Rashidi and A. Mihailidis, "A Survey on Ambient-Assisted Living Tools for Older Adults," IEEE J. Biomed. Health Inform., vol. 17, pp. 579–590, 2013.

[31] C. Rougier, J. Meunier, A. St-Arnaud, and J. Rousseau, "Robust Video Surveillance for Fall Detection Based on Human Shape Deformation," IEEE Trans. Circuits Syst. Video Technol., vol. 21, pp. 611–622, 2011.

[32] National Center for Chronic Disease Prevention and Health Promotion, "The State of Aging & Health in America 2013," CDC: Atlanta, GA, USA, 2013.

[33] G. Koshmak, A. Loutfi, and M. Linden, "Challenges and Issues in Multisensor Fusion Approach for Fall Detection: Review Paper," J. Sens., vol. 2016, pp. 1–12, 2016.

[34] G.E. Sakr, I.H. Elhajj, and H.A.-S. Huijer, "Support Vector Machines to Define and Detect Agitation Transition," IEEE Trans. Affect. Comput., vol. 1, pp. 98–108, 2010.

[35] C. Siegel and T.E. Dorner, "Information technologies for active and assisted living—Influences on the quality of life of an aging society," Int. J. Med. Inform., vol. 100, pp. 32–45, 2017.

[36] H. Matlabi, S. Parker, and K.J. McKee, "The contribution of home-based technology

to older people’s quality of life in extra care housing," BMC Geriatr., vol. 11, pp. 68, 2011.

[37] B.K. Hensel, D. Parker-Oliver, and G. Demiris, "Videophone Communication Between Residents and Family: A Case Study," J. Am. Med. Dir. Assoc., vol. 8, pp. 123–127, 2007.

[38] S. Sävenstedt, P. Sandman, and K. Zingmark, "The duality in using information and communication technology in elder care," J. Adv. Nurs., vol. 56, pp. 17–25, 2006.

[39] S. Levy and G. Steele, "End-of-Life and Living Technologies, The role of Telemedicine in palliative care of children and young people," in Proceedings of the 5th International ICST Conference on Pervasive Computing Technologies for Healthcare, Dublin, Ireland, 23–26 May 2011.

[40] M.N.K. Boulos, S. Wheeler, C. Tavares, and R.B. Jones, "How smartphones are changing the face of mobile and participatory healthcare: An overview, with examples from eCAALYX," Biomed. Eng. Online, vol. 10, pp. 1–14, 2011.

[41] V. Frisardi and B.P. Imbimbo, "Gerontechnology for demented patients: Smart homes for smart aging," J. Alzheimer Dis., vol. 23, pp. 143–146, 2011.

[42] G. Demiris and H. Thompson, "Smart homes and ambient assisted living applications: From data to knowledge—empowering or overwhelming older adults? Contribution of the IMIA Smart Homes and Ambient Assisted Living Working Group," Yearb. Med. Inform., vol. 6, pp. 51–57, 2011.

[43] R. Bemelmans, G.J. Gelderblom, P. Jonker, and L. De Witte, "Socially Assistive Robots in Elderly Care: A Systematic Review into Effects and Effectiveness," J. Am. Med. Dir. Assoc., vol. 13, pp. 114–120.e1, 2012.

[44] S.-M. Chang and H.-C. (Christina) Sung, "The effectiveness of seal-like robot therapy on mood and social interactions of older adults: A systematic review protocol," JBI Database Syst. Rev. Implement. Rep., vol. 11, pp. 68–75, 2013.

[45] C.-C. Chou, C.-P. Chang, T.-T. Lee, H.-F. Chou, and M.E. Mills, "Technology Acceptance and Quality of Life of the Elderly in a Telecare Program," CIN Comput. Inform. Nurs., vol. 31, pp. 335–342, 2013.

[46] S. Lauriks, A. Reinersmann, H.G. Van Der Roest, F. Meiland, R.J. Davies, F. Moelaert, M.D. Mulvenna, C. Nugent, and R.-M. Dröes, "Review of ICT-based services for identified unmet needs in people with dementia," Ageing Res. Rev., vol. 6, pp. 223–246, 2007.

[47] A.H. Sapci, H.A. Sapci, R. Yang, and Y. Du, "Innovative Assisted Living Tools, Remote Monitoring Technologies, Artificial Intelligence-Driven Solutions, and Robotic Systems for Aging Societies: A Systematic Review," JMIR Aging, vol. 2, pp. e15429, 2019.

[48] S. Scalvini, D. Baratti, G. Assoni, M. Zanardini, L. Comini, and P. Bernocchi, "Information and communication technology in chronic diseases: A patient’s

opportunity," J. Med. Pers., vol. 12, pp. 91–95, 2013.

[49] J. Hamm, A. Money, A. Atwal, and I. Paraskevopoulos, "Fall prevention intervention technologies: A conceptual framework and survey of the state of the art," J. Biomed. Inform., vol. 59, pp. 319–345, 2016.

[50] B.N. Ferreira, V. Guimarães, and H.S. Ferreira, "Smartphone-based fall prevention exercises," in Proceedings of the 2013 IEEE 15th International Conference on e-Health Networking, Applications and Services (Healthcom 2013), Lisbon, Portugal, 9–12 October 2013, pp. 643–647.

[51] A.F. Ambrose, G. Paul, and J.M. Hausdorff, "Risk factors for falls among older adults: A review of the literature," Maturitas, vol. 75, pp. 51–61, 2013.

[52] N. Archer, K. Keshavjee, C. Demers, and R. Lee, "Online self-management interventions for chronically ill patients: Cognitive impairment and technology issues," Int. J. Med. Inform., vol. 83, pp. 264–272, 2014.

[53] A.A.P. Wai, F.S. Fook, M. Jayachandran, Z. Song, J. Biswas, C. Nugent, M. Mulvenna, J.-E. Lee, and L.K.P. Yap, "Smart wireless continence management system for the elderly with dementia," in Proceedings of the HealthCom 2008–10th International Conference on e-health Networking, Applications and Services, Singapore, 7–9 July 2008, pp. 33–34.

[54] C. Vincent, D. Reinharz, I. Deaudelin, M. Garceau, and L.R. Talbot, "Public telesurveillance service for frail elderly living at home, outcomes, and cost evolution: A quasi-experimental design with two follow-ups," Healthc. Qual. Life Outcomes, vol. 4, pp. 41, 2006.

[55] A. Lotfi, C. Langensiepen, S.M. Mahmoud, and M.J. Akhlaghinia, "Smart homes for the elderly dementia sufferers: Identification and prediction of abnormal behavior," J. Ambient. Intell. Humaniz. Comput., vol. 3, pp. 205–218, 2011.

[56] K.L. De Ipiña, J.B. Alonso, C.M. Travieso-Gonzalez, J. Solé-Casals, H. Eguiraun, M. Faundez-Zanuy, A. Ezeiza, N. Barroso, M. Ecay-Torres, P. Martinez-Lage, et al., "On the Selection of Non-Invasive Methods Based on Speech Analysis Oriented to Automatic Alzheimer Disease Diagnosis," Sensors, vol. 13, pp. 6730–6745, 2013.

[57] ALFRED–Personal Interactive Assistant for Independent Living and Active Ageing, 2013. Available online: https://alfred.eu/downloads/index.html (accessed on 25 October 2020).

[58] Z.D. Gellis, B.L. Kenaley, and T.T. Have, "Integrated Telehealth Care for Chronic Illness and Depression in Geriatric Home Care Patients: The Integrated Telehealth Education and Activation of Mood (I-TEAM) Study," J. Am. Geriatr. Soc., vol. 62, pp. 889–895, 2014.

[59] B.E. Lyons, D. Austin, A. Seelye, J. Petersen, J. Yeargers, T. Riley, N. Sharma, N. Mattek, H. Dodge, K. Wild, et al., "Pervasive computing technologies to continuously assess Alzheimer's disease progression and intervention efficacy," Front. Aging

Neurosci., vol. 7, 2015.

[60] A.S. Hwang, K.N. Truong, J.I. Cameron, E. Lindqvist, L. Nygård, and A. Mihailidis, "Co-Designing Ambient Assisted Living (AAL) Environments: Unravelling the Situated Context of Informal Dementia Care," BioMed Res. Int., vol. 2015, 2015, 720483.

[61] B.J.J. Hattink, F.J.M. Meiland, T. Overmars-Marx, M. De Boer, P.W.G. Ebben, M. Van Blanken, S. Verhaeghe, I. Stalpers-Croeze, A. Jedlitschka, S.E. Flick, et al., "The electronic, personalizable Rosetta system for dementia care: Exploring the user-friendliness, usefulness, and impact," Disabil. Rehabil. Assist. Technol., vol. 11, pp. 61–71, 2014.

[62] D. Griol and Z. Callejas, "Mobile Conversational Agents for Context-Aware Care Applications," Cogn. Comput., vol. 8, pp. 336–356, 2015.

[63] F. Tartarini, P. Cooper, R. Fleming, and M. Batterham, "Indoor Air Temperature and Agitation of Nursing Home Residents With Dementia," Am. J. Alzheimer's Dis. Other Dementias, vol. 32, pp. 272–281, 2017.

[64] A. Alberdi, A. Weakley, M. Schmitter-Edgecombe, D.J. Cook, A. Aztiria, A. Basarab, and M. Barrenechea, "Smart home-based prediction of multidomain symptoms related to Alzheimer's disease," IEEE J. Biomed. Health Inform., vol. 22, pp. 1720–1731, 2018.

[65] A. Arcelus, C.L. Herry, R.A. Goubran, F. Knoefel, H. Sveistrup, and M. Bilodeau, "Determination of Sit-to-Stand Transfer Duration Using Bed and Floor Pressure Sequences," IEEE Trans. Biomed. Eng., vol. 56, pp. 2485–2492, 2009.

[66] J. Ocepek, A.E.K. Roberts, and G. Vidmar, "Evaluation of Treatment in the Smart Home IRIS in terms of Functional Independence and Occupational Performance and Satisfaction," Comput. Math. Methods Med., vol. 2013, pp. 1–10, 2013.

[67] M. Pastorino, A. Fioravanti, M.T. Arredondo, J.M. Cogollor, J. Rojo, M. Ferre, M. Bienkiewicz, J. Hermsdörfer, E. Fringi, and A.M. Wing, "Preliminary Evaluation of a Personal Healthcare System Prototype for Cognitive eRehabilitation in a Living Assistance Domain," Sensors, vol. 14, pp. 10213–10233, 2014.

[68] M. Lavoie, S. Routhier, A. Légaré, and J. Macoir, "Treatment of verb anomia in aphasia: Efficacy of self-administered therapy using a smart tablet," Neurocase, vol. 22, pp. 109–118, 2015.

[69] K.S. Hayward, B.A. Neibling, and R.N. Barker, "Self-Administered, Home-Based SMART (Sensorimotor Active Rehabilitation Training) Arm Training: A Single-Case Report," Am. J. Occup. Ther., vol. 69, pp. 69, 2015.

[70] M. Oliver, M.A. Teruel, J.-P. Molina, D. Romero-Ayuso, and P. González, "Ambient Intelligence Environment for Home Cognitive Telerehabilitation," Sensors, vol. 18, pp. 3671, 2018.

[71] M.J. Wade, A.S. Desai, C. Spettell, A.D. Snyder, V. McGowan-Stackewicz, P.J. Kummer, M.C. MacCoy, and R.S. Krakauer, "Telemonitoring with case management

for seniors with heart failure," Am. J. Manag. Care, vol. 17, pp. e71–e79, 2011.

[72] R. Hervás, J. Fontecha, D. Ausín, F. Castanedo, J. Bravo, and D. López-De-Ipiña, "Mobile Monitoring and Reasoning Methods to Prevent Cardiovascular Diseases," Sensors, vol. 13, pp. 6524–6541, 2013.

[73] D.E. Rifkin, J.A. Abdelmalek, C.M. Miracle, C. Low, R. Barsotti, P. Rios, C. Stepnowsky, and Z. Agha, "Linking clinic and home: A randomized, controlled clinical effectiveness trial of real-time, wireless blood pressure monitoring for older patients with kidney disease and hypertension," Blood Press Monit., vol. 18, pp. 8–15, 2013.

[74] G. Sun, G. Shinji, Z. Zhao, S. Kim, S. Suzuki, N. Imamoglu, W. Yu, and T. Matsui, "Vital-CUBE: A non-contact vital sign monitoring system using medical radar for ubiquitous home healthcare," J. Med. Imaging Health Inform., vol. 4, p. 1166, 2014.

[75] E. Kańtoch, "Recognition of Sedentary Behavior by Machine Learning Analysis of Wearable Sensors during Activities of Daily Living for Telemedical Assessment of Cardiovascular Risk," Sensors, vol. 18, pp. 3219, 2018.

[76] European Commission, "The EU-Funded Project CommonWell: How to Integrate Health and Social Care with ICT," 2013. Available online: https://ec.europa.eu/digital-single-market/en/news/eu-funded-project-commonwell-how-integrate-health-and-social-care-ict (accessed on 1 September 2020).

[77] N.C. Antoniades, P.D. Rochford, J.J. Pretto, R.J. Pierce, J. Gogler, J. Steinkrug, K. Sharpe, and C.F. McDonald, "Pilot Study of Remote Telemonitoring in COPD," Telemed. e-Health, vol. 18, pp. 634–640, 2012.

[78] C. Pedone, D. Chiurco, S. Scarlata, and R.A. Incalzi, "Efficacy of multiparametric telemonitoring on respiratory outcomes in elderly people with COPD: A randomized controlled trial," BMC Health Serv. Res., vol. 13, p. 82, 2013.

[79] D.O. Johnson, R.H. Cuijpers, J.F. Juola, E. Torta, M. Simonov, A. Frisiello, M. Bazzani, W. Yan, C. Weber, S. Wermter, et al., "Socially Assistive Robots: A Comprehensive Approach to Extending Independent Living," Int. J. Soc. Robot., vol. 6, pp. 195–211, 2013.

[80] C. Sicotte, G. Paré, S. Morin, J. Potvin, and M.-P. Moreault, "Effects of Home Telemonitoring to Support Improved Care for Chronic Obstructive Pulmonary Diseases," Telemed. e-Health, vol. 17, pp. 95–103, 2011.

[81] B. O. A. Henkemans, W. A. Rogers, A. D. Fisk, M. A. Neerincx, J. Lindenberg, and C. A. P. G. van der Mast, "Usability of an adaptive computer assistant that improves self-care and health literacy of older adults," Methods Inf. Med., vol. 47, pp. 82–88, 2008.

[82] D. Charron-Prochownik, J. C. Zgibor, M. Peyrot, M. Peeples, J. McWilliams, J. Koshinsky, W. Noullet, and L. M. Siminerio, "The diabetes self-management

assessment report tool (D-SMART®) process evaluation and patient satisfaction," Diabetes Educ., vol. 8, pp. 833–838, 2007.

[83] R. Costa, P. Novais, L. Lima, J. B. Cruz, and J. Neves, "VirtualECare: Group Support in Collaborative Networks Organizations for Digital Homecare," in Handbook of Digital Homecare, Springer, Berlin/Heidelberg, Germany, 2009, pp. 151–178.

[84] K. A. Earle, R. S. Istepanian, K. Zitouni, A. Sungoor, and B. Tang, "Mobile Telemonitoring for Achieving Tighter Targets of Blood Pressure Control in Patients with Complicated Diabetes: A Pilot Study," Diabetes Technol. Ther., vol. 12, pp. 575–579, 2010.

[85] P. Salvo, N. Calisi, B. Melai, V. Dini, C. Paoletti, T. Lomonaco, A. Pucci, F. Di Francesco, A. Piaggesi, and M. Romanelli, "Temperature- and pH-sensitive wearable materials for monitoring foot ulcers," Int. J. Nanomed., vol. 12, pp. 949–954, 2017.

[86] M. Kępski and B. Kwolek, "Unobtrusive Fall Detection at Home Using Kinect Sensor," in Comput. Vis., 2013, vol. 8047, pp. 457–464.

[87] J. He, C. Hu, and Y. Li, "An Autonomous Fall Detection and Alerting System Based on Mobile and Ubiquitous Computing," in Proceedings of the 2013 IEEE 10th International Conference on Ubiquitous Intelligence and Computing and 2013 IEEE 10th International Conference on Autonomic and Trusted Computing, Vietri sul Mere, Italy, 18–21 December 2013, pp. 539–543.

[88] S. Abbate, M. Avvenuti, F. Bonatesta, G. Cola, P. Corsini, and A. Vecchio, "A smartphone-based fall detection system," Pervasive Mob. Comput., vol. 8, pp. 883-899, 2012.

[89] S. Abbate, M. Avvenuti, and J. Light, "MIMS: A Minimally Invasive Monitoring Sensor Platform," IEEE Sens. J., vol. 12, pp. 677-684, 2011.

[90] M. Terroso, R. Freitas, R. Simoes, J. Gabriel, and A.T. Marques, "Active assistance for senior healthcare: A wearable system for fall detection," in Proc. 8th Iberian Conf. on Information Systems and Technologies, Lisboa, Portugal, June 19-22, 2013.

[91] J. Cabestany, J.M. Moreno, C. Pérez, A. Samà, A. Català, A. Rodriguez-Molinero, and M. Arnal, "FATE: One step towards an automatic aging people fall detection service," in Proc. 20th International Conference on Mixed Design of Integrated Circuits and Systems, Gdynia, Poland, June 20-22, 2013.

[92] J. Wang, Z. Zhang, B. Li, S. Lee, and R.S. Sherratt, "An enhanced fall detection system for elderly person monitoring using consumer home networks," in IEEE Trans. Consum. Electron., vol. 60, pp. 23-29, 2014.

[93] M. Brell, J. Meyer, T. Frenken, and A. Hein, "A mobile robot for self-selected gait velocity assessments in assistive environments," in Proceedings of the 3rd International Conference on High Confidence Networked Systems, Berlin, Germany, 15-17 April 2014.

[94] W.D. Kearns, J.L. Fozard, M. Becker, J.M. Jasiewicz, J.D. Craighead, L. Holtsclaw, and

C. Dion, "Path tortuosity in everyday movements of elderly persons increases fall prediction beyond knowledge of fall history, medication use, and standardized gait and balance assessments," J. Am. Med. Dir. Assoc., vol. 13, pp. 665.e7–665.e13, 2012.

[95] M. Ferrari, B. Harrison, O. Rawashdeh, M. Rawashdeh, R. Hammond, and M. Maddens, "A pilot study testing a fall prevention intervention for older adults: Determining the feasibility of a five-sensor motion detection system," J. Gerontol. Nurs., vol. 38, pp. 13–16, 2011.

[96] A.J.A. Majumder, I. Zerin, M. Uddin, S.I. Ahmed, and R.O. Smith, "SmartPrediction: A real-time smartphone-based fall risk prediction and prevention system," in Proceedings of the 2013 Conference on Research in Adaptive and Convergent Systems, Montreal, QC, Canada, 1–4 October 2013, pp. 434–439.

[97] A. Staranowicz, G.R. Brown, and G.-L. Mariottini, "Evaluating the accuracy of a mobile Kinect-based gait-monitoring system for fall prediction," in Proceedings of the 6th International Conference on Bioinformatics and Biomedical Science, Singapore, 22–24 June 2017, pp. 1–4.

[98] S. Almer, J. Kolbitsch, J. Oberzaucher, and M. Ebner, "Assessment Test Framework for Collecting and Evaluating Fall-Related Data Using Mobile Devices," in Mining Data for Financial Applications, 2012, pp. 83-90.

[99] A. Weiss, M. Brozgol, M. Dorfman, T. Herman, S. Shema, N. Giladi, and J. M. Hausdorff, "Does the Evaluation of Gait Quality During Daily Life Provide Insight Into Fall Risk? A Novel Approach Using 3-Day Accelerometer Recordings," in Neurorehabilitation and Neural Repair, vol. 27, 2013, pp. 742-752.

[100] W. Zhang, G. R. H. Regterschot, F. Wahle, H. Geraedts, H. Baldus, and W. Zijlstra, "Chair rise transfer detection and analysis using a pendant sensor: An algorithm for fall risk assessment in older people," in Proceedings of the 2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, Chicago, IL, USA, 26-30 August 2014, vol. 2014, pp. 1830-1834.

[101] G. Forbes, S. Massie, and S. Craw, "Fall prediction using behavioral modeling from sensor data in smart homes," Artificial Intelligence Review, vol. 53, pp. 1071-1091, 2020.

[102] Y. Shi, Y.C. Shi, and X. Wang, "Fall detection on mobile phones using features from a five-phase model," in Proceedings of the 9th International Conference on Ubiquitous Intelligence & Computing and 9th International Conference on Autonomic & Trusted Computing, Fukuoka, Japan, 4-7 September 2012, pp. 951-956.

[103] W.-C. Chou, W.-Y. Lin, M.-Y. Lee, and K.F. Lei, "Design and Assessment of a Real-Time Accelerometer-Based Lying-to-Sit Sensing System for Bed Fall Prevention," in Proceedings of the 2013 IEEE International Conference on Systems, Man, and Cybernetics, Manchester, UK, 13-16 October 2013, pp. 1471-1475.

[104] E.T. Horta, I.C. Lopes, J.J.P.C. Rodrigues, and S. Misra, "Real time falls prevention and detection with biofeedback monitoring solution for mobile environments," in Proceedings of the 2013 IEEE 15th International Conference on e-Health Networking, Applications and Services (Healthcom 2013), Lisbon, Portugal, 9-12 October 2013, pp. 594-600.

[105] C. Siegel, B. Prazak-Aram, J. Kropf, M. Kundi, and T.E. Dorner, "Evaluation of a modular scalable system for silver-ager located in assisted living homes in Austria—study protocol of the ModuLAAr ambient assisted living project," BMC Public Health, vol. 14, p. 736, 2014.

[106] I-DONT-FALL, "Integrated Prevention and Detection Solutions Tailored to the Population and Risk Factors Associated with FALLs," 2015. Available online: https://portal.singularlogic.eu/en/eu-project/7938/idontfall (accessed on 1 September 2020).

[107] Y.J. Gschwind et al., "ICT-based system to predict and prevent falls (iStoppFalls): Results from an international multicenter randomized controlled trial," Eur. Rev. Aging Phys. Act., vol. 12, pp. 1-11, 2015.

[108] ReAAL Project, "European Commission within the ICT Policy Support Programme," 2016. Available online: https://www.aal.fraunhofer.de/en/projekte/reaal.html (accessed on 1 September 2020).

[109] Liu, L.; Stroulia, E.; Nikolaidis, I.; Miguel-Cruz, A.; Rincon, A.R. "Smart homes and home health monitoring technologies for older adults: A systematic review." Int. J. Med. Inform. 2016, 91, 44–59.

[110] A. Mitseva, A. Litke, N. Papadakis, and N. Prasad, "ISISEMD intelligent system for independent living," J. Inf. Technol. Healthc., vol. 7, 2009.

[111] B. Upatising, G. J. Hanson, Y. L. Kim, S. S. Cha, Y. Yih, and P. Y. Takahashi, "Effects of home telemonitoring on transitions between frailty states and death for older adults: A randomized controlled trial," Int. J. Gen. Med., vol. 6, 2013.]

[112] R. Rajagopalan, I. Litvan, and T.-P. Jung, "Fall prediction and prevention systems: Recent trends, challenges, and future research directions," Sensors, vol. 17, 2017.

[113] S. Majumder, T. Mondal, and M. J. Deen, "Wearable Sensors for Remote Health Monitoring," Sensors, vol. 17, 2017.

[114] B. Klimova and P. Maresova, "Wearable and Portable Monitoring Devices for Older People," in Advanced Multimedia and Ubiquitous Engineering, vol. 448. Springer, 2017, pp. 446-451.

[115] O. Vermesan et al., "Internet of Things Cognitive Transformation Technology Research Trends and Applications," in Cognitive Hyperconnected Digital Transformation: Internet of Things Intelligence Evolution, J. Bacquet and O. Vermesan, Eds., River Pubs., Trondheim, Norway, 2017, pp. 17-95.]

Chapter 4: Methodology for the Development of Residential Learning Healthcare Systems with Edge Computing

This chapter is part of a position paper that has been published in IEEE Transactions on Consumer Electronics Journal with the title: “Requirements for Adaptive Consumer Gateways in Residential Learning Healthcare Systems: Bringing Intelligence to the Edge”.

N. Fares and R. S. Sherratt, "Requirements for Adaptive Consumer Gateways in Residential Learning Healthcare Systems: Bringing Intelligence to the Edge," in IEEE Transactions on Consumer Electronics, doi: 10.1109/TCE.2023.3326570.

The Internet of Things (IoT) is developing at a rapid growth and being integrated into several Information and Communication Technology (ICT) solutions. IoT technology is increasingly being incorporated into healthcare systems, and widely achieving a growing acceptance in different aspects of daily life [1]. Presently, an evolution from hospital-centered healthcare systems to hospital-home-balanced healthcare systems is in its early stages aiming to become someday home-centered healthcare systems [2]. But for such an evolution to develop further, new technologies, system architectures, and computing paradigms are required. And, with the development of this evolution towards Learning Healthcare Systems (LHS), new challenges occur in system reliability, interoperability, low latency response, energy efficiency, mobility, security, and privacy become requirements to fulfill. This extension of healthcare boundaries outside the hospital settings, into the consumer domain, aims for the early detection and prevention of health deterioration and permitting consumers to live independently at home, allowing people with acute diseases and at-risk populations as senior adults to be continuously monitored and guided by healthcare providers [3], wardens or family members, and to receive advice on their healthcare.

In general, an ICT healthcare system architecture consists of three main tiers in the context of IoT, a Wireless Body Area Network (WBAN), a gateway device located in the vicinity of the WBAN (i.e., edge) allowing continuous connectivity between different components of the ICT healthcare system, and a cloud server performing continuous data analysis and enabling real-time decision making. Fares *et al*. [4] presented a detailed explanation of ICT healthcare systems, but with Internet connectivity causing a limitation to the performance of such systems, particularly in many places in the world, and the prohibitive cost of such systems, significant research is currently in progress with the aim of adjusting the functionalities of each tier to enable real-time decision making locally at the edge.

Gateways can play a key role in smart healthcare monitoring and real-time decision making by storing and utilizing healthcare data locally and to enable the monitoring and decision-making process to be more patient/consumer oriented. Traditionally, home healthcare gateways have acted as a hub between the body, personal, local area networks, and remote healthcare cloud services. But the fact that a gateway's characteristics of processing power, power consumption, and communication bandwidth are developing with technological advancements can empower the role of the gateway through strengthening its processing power, intelligence and masterminded network capabilities leading to the creation of a *smart learning healthcare gateway*. This upgrade in the gateway's functionalities enhances healthcare ICT system's architecture in terms of scalability, energy-efficiency, reliability, and interoperability. To enable these enhancements in the architecture of the gateway, edge computing is required. That involves the creation of a computation layer that permits bringing intelligence to the edge and enables the communication between the sensors layer and the cloud layer [5, 6].

Another limitation to the performance of healthcare ICT solutions is the availability, usability, and timeliness of comprehensive data sources to achieve optimal healthcare experience for both healthcare providers and consumers. Innovations in the availability and application of data, including tools as predictive analytics, Clinical Decision Support (CDS), and other knowledge management systems, can precipitate the transmission from healthcare documentation to healthcare practice, identify breaches in healthcare, and target interventions to the appropriate populations.

Research into healthcare-based consumer devices has been a hot topic ever since the IEEE International Conference on Consumer Electronics, back in 2009, with healthcare as the conference theme. Since then, many useful, practical, consumer systems have emerged and will be discussed in this chapter. However, this chapter now calls for a paradigm shift from the current fixed patient/consumer-based healthcare ICT systems to a *Learning Healthcare System* (LHS) with a resilient data infrastructure to provide real-time access to knowledge and automated record of the healthcare experience as called upon by the US Institute of Medicine [7] back in 2007. A LHS comprehensively brings together information about the healthcare provided and its pursuing outcomes to advise innovation in healthcare delivery and to develop new scientific assumptions. Such systems can adapt to the consumers' changing needs over time. This is important because patients/consumers could purchase home healthcare LHS gateways, but as the patient's/consumer's needs change then the gateway can also adapt. Costs can be minimized by having standard gateways with adaptation supplied by software. This transformation requires the re-engineering of multiple areas of the healthcare system: science and informatics, patient and care provider collaboration, transparency and value of healthcare outcomes, and development and maintenance of continuous learning community [8].

LHS is a significant evolution from Evidence-Based Medicine (EBM). Greater awareness of LHS is necessary to achieve success in the goal of delivering precision and personalized care. LHS, as described by Institute of Medicine, is a system in which "*knowledge generation is embedded into the core of the practice of medicine that it is a natural outgrowth and product of the healthcare delivery process and leads to continual improvement in care*" [9, 10]. Friedman *et al*. [11] described LHS as a system which progress in science, informatics and care culture align to generate new knowledge as an ongoing natural by-product of the care experience, and seamlessly refine and deliver best practices for continuous improvement in health and healthcare.

Although the transformation of healthcare into LHSs is still in an early stage, several examples of LHS models have emerged and will be discussed later in this chapter.

LHS was first defined in 2007 by Etheredge [1] to be technology frameworks that put major emphasis on the inclusion of patients in decision making to personalize care plans. In healthcare, linking available biomedical and environmental data sources gives rise to variety and heterogeneity of data. Data sources vary between quantitative data as biomedical sensor data, environmental sensor data, laboratory tests, images, and qualitative data as statistics and free text. Integrating these data sources with mobile and social health to address acute and chronic diseases is the future of LHS. This chapter discusses LHS pillars, LHS architectures, and possible data sources used in LHS [12, 13].

4.1 LHS Taxonomy

Lambin *et al*. [14] modeled LHS to embrace four sequential and infinitely repeated phases for the development of a Decision Support System (DSS) that focuses on prediction model development, validation, and implementation to enhance patient quality of life and preferences, comorbidity, and cost effectiveness. The four phases consist of a data phase that collects and mines data from various sources, a knowledge phase that exploits knowledge from the collected data through implementing complex analytical methods as machine learning, an application phase that employs the knowledge gained to enhance healthcare delivery, and finally an evaluation phase that analyses the DSS performance. Lambin *et al*. emphasized the need for data sharing ethos to overcome the limitations of accessing data with sufficient fidelity in relation to its veracity, velocity, variety, and volume in LHS. Thus, a federated system that ensures public trust is needed to mine data in one or several locations based on a policy framework where only organizations and individuals that are members of a learning healthcare system are eligible to have access to data. CancerLinQ[1] [15], of the American Society of Clinical Oncology (ASCO) is one of the initiatives to achieve this goal. CancerLinQ used a data centralization approach that faces classical barriers to data sharing as human resources; cultural and language difficulties; political and academic relevance; legal and privacy issues, etc. [14]. And, to overcome the traditional barriers of centralized data sharing proposed by CancerLinQ, novel applications for advanced information communication technologies were developed in the euroCAT project[2] under the title of distributed learning which forced the development of data with semantic interoperability (machine-readable data).

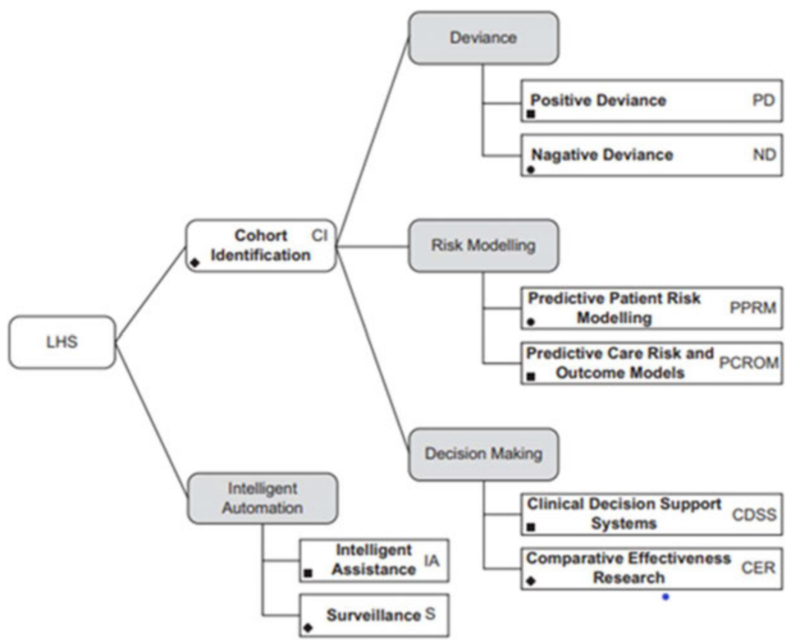

Figure 4.1: Learning Healthcare Systems Taxonomy [12].

Few papers discuss the LHS Taxonomy [16-18]. The Heimdall-integrated LHS framework unified the knowledge identified from all three papers into a taxonomy of

[1] http://cancerlinq.org/
[2] www.eurocat.info

nine LHS classification types shown in ***Figure 4.1***. Cohort Identification (CI) the first operational step in LHS that tails patients with similar traits to reveal the efficiency and effectiveness of a medical approach. Deviance evaluates clinical care by analyzing CI data and is branched into Positive Deviance (PD) and Negative Deviance (ND). PD recognizes beneficial behaviors for inclusion in future clinical practice and identifies common characteristics of patients benefiting from a treatment and defines patient groups that may benefit from the same intervention. ND determines clinical behaviors that negatively affected patient care and the resulting outcome. Risk modelling analyzes the CI data for patient and clinical care risks and develops predictive models for each. Predictive Patient Risk Modelling (PPRM) identifies groups at higher risk for future critical unhealthy events by using patterns discovered in patient datasets. Predictive Care Risk and Outcome Model (PCROM) algorithms identify situations of high risk resulting from unsafe, delayed, or inefficient care, determine measures of the effectiveness of various interventions. Decision making is performed based on CI data. Clinical Decision Support Systems (CDSSs) are active knowledge systems that connect two or more characteristics of the patient to computerized knowledge bases with algorithms to produce patient-specific treatment plans. Comparative Effectiveness Research (CER) compares interventions and outcomes within an Electronic Health Record (EHR) dataset to determine the most effective treatment. CER identifies patients with similar characteristics to the current patient, restoring knowledge on treatments that propose optimal health outcomes.

Intelligent automation makes use of various sources of data such as research data and EHR data and involves Intelligent Assistance (IA) and Surveillance (S). IA uses data sources to computerize routine procedures such as clinical notes or summing up patient health condition before consultations. Surveillance (S) monitors EHR data for outbursts of diseases or treatment issues as unhealthy medications or increased frequency for post-surgical infections [10, 12].

The Heimdall-integrated LHS framework started from these nine LHS classification types to record, store, index and present information that flows into and improve the learning processes in Evidence-Based Medicine (EBM) towards delivery of Precision Medicine (PM). This enables the achievement of unique individualized patient decision practices in LHSs [12].

McLachlan *et al*. [19] discussed barriers to LHS implementation. The most common are cost [20], data interoperability and standardization [21], poor data quality and integrity [22], informed consent and ethics review complications [23], privacy and security issues [24] and slow technology adoption [25]. These issues are seen in the same context for adopting EHR/EMR. And since EHR/EMR is a major data source for LHS, this indicates LHS is inheriting problems from the EHR/EMR. Thus, adopting Heimdall taxonomy and framework that classifies and describes LHS is a major requirement in the development of LHS systems to improve the focus on the individual consumer's health, bringing efficient and expedient PM solutions [10, 12].

4.2 Data Sources in LHS

In healthcare, there is a need to improve the information infrastructure of healthcare systems and to better understand the characteristics that provoke what data needs to be collected. Concatenating various biomedical and environmental data sources available results in data heterogeneity and variety that support the basis for observational evidence to answer clinical questions, address acute and chronic diseases, deliver PM by identifying unique individualized care plans, and maintain public trust in the use of data. The fundamental routine data sources include the EHRs, clinical registries, and administrative claims data. In addition to these data sources, data collected from consumers and the environment also provide unique and complementary information to support healthcare. Each data source has strengths and limitations but can, especially in combination, begin to provide a comprehensive view of the patient care experience necessary for the LHS.

The EHR data source is becoming increasingly available because of the spread of both inpatient and outpatient EHR systems. Weiner and Embi [26] claimed that EHR data provides more details on patient-level medical issues than administrative claims or other data sources. Immediate availability of data in EHRs permits its use in real-time for clinical care, thus enabling point-of-care CDS, patient risk estimation, and patient emergency alerts which are main pillars of the LHS taxonomy [27]. Although EHR data fundamentally increases the effectiveness of care in LHS, there is still a need to tackle a set of existing challenges. Such challenges include missing data, inaccurate data, uninterpretable data, inconsistencies among different EHR data providers due to different and poorly integrated EHR system. These challenges and limitations, create the need for the development of optimal EHR user interfaces to minimize the deleterious effects of EHR-clinician interaction and improve the ease and consistency of data entry to reduce user burden and decrease the amount of unstructured, uninterpretable data in the EHR [28, 29]. In addition, there is a need to structure and remodel the available EHR data using Machine Learning (ML) algorithms to enable different forms of feature extraction as simple concept, temporal, and relation extraction features. Neural networks and deep learning ML algorithms such as the Recursive Neural Network (RNN) and AutoEncoders have been shown to produce impressive results on a variety of Neuro Linguistic Programming (NLP) tasks in many domains of EHR data analysis [30].

Clinical registries are another important source of data for the LHS. It is regarded as quantitative databases of clinical conditions or therapies. The clinical registries' main role is to capture important details about specific conditions, procedures, or populations to analyze and enhance quality and outcomes [13]. The main distinction between EHRs and clinical registry databases is that clinical registry databases entail data collected from a diverse cohort of patients, whereas EHRs embrace data provided by individuals [31]. Clinical registries have a number of limitations such as the presence of a time lag between care delivery and collection of data, the focus on single conditions or treatments, the inconsistent participation of targeted patients and health systems, and the low quality of clinical registries data since this form of data is primarily designed for financial/billing purposes making it challenging for clinical data mining [32].

Administrative claims data, created from healthcare invoices to payers, are the most extensively available data in healthcare systems. Claims can be useful for inspecting disease occurrence, management, and consequences as in clinical registries. Claims provide important visions for hospitals, healthcare systems, and payers since they are linked to a payer and not to a single EHR or clinical registry. Claims data have limitations like all other data sources. Claim data depend on authentic coding of clinical conditions and events. Claim data lack critical clinical details such as indications for procedures, disease severity measures, and other clinical information necessary for accurate risk adjustment and correct characterization of clinical outcomes [33].

Complementary data sources enabled the collection of healthcare data from pervasive and unobtrusive sensing technologies. Such technologies are wearable, implantable, and ambient sensors. Complementary data sources may be classified into patient-reported data and environmental data. Patient-reported data provides information on the patient's health status and physiological measures which can be collected using implantable medical devices and/or wearables. Gathering and integrating data from complementary data sources can contribute to more comprehensive evaluation of a person's health and permits proactive awareness to declines or improvements in health. Although complementary data sources are more likely to be incomplete in areas of lower socioeconomic status, and poor Internet connection, such data sources are important for LHS development and effectiveness, where significant effort is needed to develop methods for collection, analysis, and use of such data. Different machine learning algorithms can be applied on sensor data at different stages for the detection, prediction, and prevention of medical conditions or for real-time decision making in residential healthcare systems. Clustering machine learning algorithms are used for data compression. Classification machine learning algorithms are used for data mining. Neural networks and deep learning algorithms are applied for detailed analysis and knowledge extraction. And finally, ensemble learning algorithms are applied in combination with neural network algorithms for superior results in decision making [34].

4.3 Gateways in LHS

Healthcare IoT-based ICT systems are well-defined to sustain health applications, mainly early detection and prediction involving both patient and healthcare providers. The complexity of such healthcare ICT systems varies from simple to complex IoT-based monitoring systems. Simple systems introduced starting 2009 are traditional systems with fixed gateways that execute only data collection, transmission, and visualization [35, 36]. Many simple consumer oriented smart IoT gateways have been proposed since then, but unfortunately, they are still fixed, nonadaptive, and with no intelligence introduced at the edge. The proposed gateways discussed data collection [37], data transmission [38, 39], data routing [40], and data privacy [41]. Sanchez *et al.* [41] introduced social applications to home gateways by implementing a Social Enabler (SE) for retrieving and presenting content, and a Social Watchdog to ensure security and privacy of the consumer. Tung *et al*. [39] designed a homecare gateway introducing novelty in the development of a dual radio ZigBee sensor network to increase transmission data rate, and a medical application unit for automatic service discovery. Ray *et al*. [40] developed an IoT-edge gateway applying smartness by implementing a novel consumer's wellness data-routing algorithm. Dey *et al.* [41] presented an electrocardiogram (ECG) based home monitoring for consumer networks.

Starting 2015, complex monitoring systems were introduced involving more advanced smart gateways that establish intelligent services using data analytic methods diverting from rule-based methods to various learning algorithms [42-44]. Complex IoT-based monitoring systems are generally categorized into cloud-based IoT systems and fog-based IoT systems.

In cloud-based systems with smart gateways in healthcare [42], data analytics is conventionally performed on the cloud where the gateway is a virtual platform that connects sensors, IoT modules, and smart devices to the cloud [45-47]. Hung *et al*. [46] and Yan *et al*. [48] introduced healthcare systems where data analysis is performed at a remote data center. Centralization in cloud-based systems benefits health services and biomedical research by saving time (to access and retrieve data) and cost, collaboration between medical staff (sharing medical resources, data, and files anywhere and anytime) and virtualization. But centralization causes drawbacks as making monitoring systems critically reliable on network availability and security. Any interruption in the Internet connection may lead to flows in the monitoring and decision-making services of the monitoring systems. And any violation in the security and privacy of patients' medical data and personal information caused by centralized computing affects the patient's trust and Quality of Service (QoS) provided. Although, privacy can be enhanced by distributing information across a fog [49], and network availability may be enhanced by focusing more on abstraction or mechanism enforcing by improving network performance through providing delay and bandwidth guarantees [50]. Centralized architecture in cloud computing in healthcare showed to cause high data retrieval times for real-time emergency scenarios and high-power consumption and costs associated with sending data to the cloud for computation, especially large amounts of data generated by sensors. Finally, cloud-based healthcare solutions do not offer a low-cost mobile environment to the consumer, that is necessary for many monitoring scenarios [44].

Fog-based IoT systems with smart gateways on the edge in healthcare extends the cloud computing paradigm to the edge of the network enabling new services for local computation, storage, and control for healthcare IoT systems. In fog-based IoT-systems an intermediate layer of networked smart gateways is formed at the edge between sensors and the Cloud. Edge-based computing proved to fulfill modern healthcare ICT systems' requirements for reduced latency in time-dependent solutions [51], energy efficiency [52], higher level of security and privacy [53], more accurate location awareness [54], and easier usability [44, 55]. Edge computing outperforms cloud computing in terms of energy efficiency by developing or applying encryption schemes and classification techniques consuming less threshold power [56, 57], implementing edge mining [56], and resource management by determining when and which tasks are to be offloaded to the Cloud [58]. Lee *et al*. [57] developed a consumer oriented smart healthcare monitoring system at the edge with low complexity, high resolution, and low power consumption. Intelligence was introduced by implementing a wavelet-based classification machine learning algorithm at the edge for waveform discrimination.

Edge computing uses authentication protocols and trust ratings and introduces new methods for obtaining patient's information through the distribution of only vital information to obtain a higher level of privacy [49] and uses identity-based encryption techniques supported by outsourcing decryption to enable the shift of the computational burden to the edge at a lower latency cost and throughput overhead to assure low-cost consumption in patient's data privacy and security [59]. Edge computing uses localization techniques with a higher level of accuracy varying from a single room to multiple room localization awareness within a single home [54]. Finally, edge computing devices in healthcare as smartphones and ambient and wearable sensors are designed to be simple and user-friendly for untrained personnel and patients to use correctly for accurate data transmission [44]. Rachakonda *et al*. [60] developed an intelligent edge device for stress level detection that received a novel consumer electronic proof of concept with Deep Neural Networks (DNN) deployed on edge devices, and a fully automated edge-based monitoring device to distinguish stress-eating from normal eating using a set of clustering and classification machine learning algorithms [61]. Both healthcare edge-based systems use single board computer (SBC) and smartphone edge platforms where machine learning models are executed on the SBC with real-time datasets, that are sent also to the cloud for future analysis.

Although it's proven that edge computing provides many beneficial requirements to healthcare, a couple of limitations need to be addressed. In edge computing, resource management techniques are bounded due to the limited computational capacity at the edge nodes. This disallows the implementation of powerful machine learning algorithms for local decision making at the edge nodes. This limited computational capacity may lead to a degradation in the QoS and Quality of Experience (QoE) of the system due to the less powerfulness and sophistication of edge-based algorithms over cloud-based ones [16, 44].

In conclusion, merging cloud-based and fog-based healthcare ICT systems is beneficial for monitoring and decision making, but independently their applications are insufficient due to their architectural limitations. Thus, homogenizing both computing paradigms permits maximizing the best features provided by both designs and reducing their limitations [16].

4.4 Machine Learning in LHS

Machine learning plays a fundamental role in the development in LHS [62]. The consumer healthcare field can benefit from various ML algorithms that can help in the identification/monitoring of different diseases, recommendations, and guidance for consumers' daily activities and healthcare procedures. This includes the identification of high risk for medical emergencies such as relapse in health condition or transition into a higher disease state. An ML method used in LHS will likely contain a library of information that includes some or all of test data, diagnosis, patient medical data, sensor data, etc. for better decision making and improving the health condition and quality of life of patients.

There is a diverse collection of ML algorithms that can be implemented for the development of smart LHSs supporting clinical decision making for diagnosis, prognosis, or treatment selection [63]. The performance of a learning healthcare system and its prediction accuracy is affected by the choice of the algorithm and the quality and quantity of data used. ***Figure 4.2*** presents a hierarchal representation of ML algorithms suitable for LHSs.

ML algorithms are categorized into classical learning algorithms, neural networks and deep learning algorithms, reinforcement learning algorithms, and ensemble learning algorithms. Classical ML approaches can be broadly divided into two major categories: supervised and unsupervised learning. Supervised learning tasks include regression and classification, with algorithms including logistic regression, linear regression, Bayesian Networks (BN), and Support Vector Machines (SVM). Regression algorithms are used to predict the onset of chronic diseases such as diabetes [64] or lung cancer within a period of time based on an identified collection of predictors. Classification is one of the most widely used methods of data mining in healthcare organizations [65]. Classification

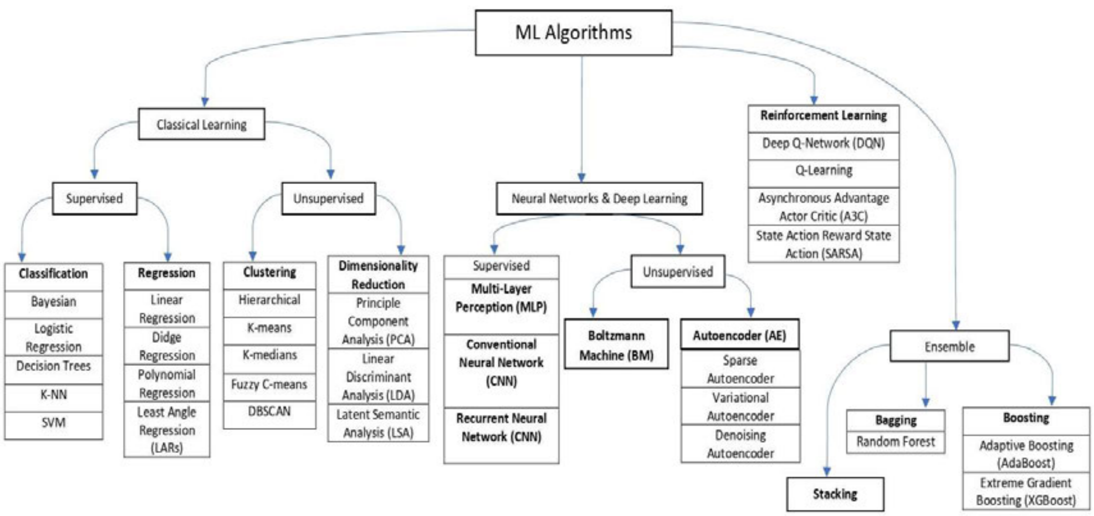

Figure 4.2. Hierarchal representation of Machine Learning Algorithms.

algorithms are used for disease prediction [66]; if a tumor is benign or malignant through image recognition, or the presence of mental health condition by language processing. In supervised learning approaches, once a dataset has been organized into features and outcomes, a classification or regression ML algorithm is applied to it. The algorithm is iteratively improved to reduce the error of prediction using an optimization technique. SVM is one of the most popular approaches that are used by researchers in healthcare field for classification [67, 68]. SVM has the advantages of increasing class separation and reducing expected prediction error, flexible for both linear and nonlinear-based discriminatory analyses, and it is suitable for analysis of high-dimensionality datasets with small sample size when combining with feature selection approaches [69]. Seint *et al*. [70] proposed the use of a SVM model for automatic understanding of medication and meal intake monitoring.

In unsupervised learning, patterns are sought by algorithms without any input from the user. Unsupervised techniques are exploratory and used to find undefined patterns or clusters which occur within datasets. Unsupervised algorithms categorized into clustering algorithms as hierarchal clustering, k-means, and fuzzy c-means, or dimension reduction algorithms used for compression of information in datasets into fewer features, or dimensions to avoid issues as multiple collinearity or high computational cost [71]. Kalatzis *et al*. [72] showed that interactive dimensionality reduction and K-means improve patient adherence in remote healthcare monitoring. Dhiviya *et al*. [73] concluded that clustering is best used for the management of communication delay and energy consumption by sensor nodes in a healthcare monitoring system.

Neural networks and deep learning algorithms are another subset of ML that involves a number of nonlinear transformations and outperform traditional methods in speech recognition, visual disease recognition, and disease detection [74]. Deep learning models as Convolutional Neural Network (CNN), Deep Neural Networks (DNN) [60, 64] and Recurrent Neural Networks (RNN) [75] consist of multiple processing layers that are capable of learning meaningful features of the raw data without domain level expertise as in conventional machine learning methods. Lately, neural networks are introduced in various healthcare monitoring systems. Joshi *et al*. [64] proposed the use of DNN for glucose sensor calibration in a new wearable device for glucose measurement. Rachakonda *et al.* [60] used a DNN for stress detection. Ding and Wang [75] used an RNN for classifying human motion and identifying falling incidents automatically.

Ensemble learning methods use multiple classifiers (or classification models) working together to yield to better classification accuracy than the use of a single classifier. Several studies demonstrate that ensemble approaches can improve classification performance in the biomedical and healthcare fields [76]. Liaqat *et al.* [77] proposed a novel ensemble classification algorithm for multiple activity recognition of elderly people. The proposed algorithm outperformed multilayer perceptron, CNN, KNN, logistic regression and SVM in human activity classification. AdaBoost and random forest are examples of ensemble learning methods that are currently most widely used with SVM and show the best classification performance in various cancer detection scenarios [78].

Reinforcement learning is based on the methodology by which infants learn to interpret the world around them. It comprises of a set of algorithms such as Q Learning and State-Action-Reward-State-Action (SARSA) that functions by selecting the action with the highest reward in each state. Such algorithms are used in home healthcare monitoring systems to prioritize urgent messages to ensure emergency situations are handled on time [79]. Zhou *et al.* [80] developed an intelligent auto labeling scheme for sensors based on Q-learning to improve the learning efficiency in human activity recognition.

In order to identify which ML algorithms to implement in an LHS, the designer needs to identify whether the purpose of use is for detection, prevention of emergencies, or long-term management of health conditions. Then the selection of the ML algorithm should be based on its performance in terms of accuracy, sensitivity, specificity, and precision. Based on the literature, SVM, random forest algorithm, neural network algorithms performed better in analyzing features such as time and frequency domain features, multi-type feature vector, numerical features, and images [81, 82]. Of course, an adaptive gateway can have its software changed over time, thus the system can adapt from detection to management of long-term care when applicable.

References

[1] L. M. Etheredge, “A rapid-learning health system,” *Health Affairs*, vol. 26, no. 2, pp. w107–w118, 2007, doi: 10.1377/hlthaff.26.2.w107.

[2] P. P. Reid, W. D. Compton, J. H. Grossman, and G. Fanjiang, "Building a better delivery system: A new engineering/health care partnership," in *A Framework for a Systems Approach to Health Care Delivery*, National Academies Press, USA, 2005. Available: https://www.ncbi.nlm.nih.gov/books/NBK22878.

[3] J. L. Clarke, S. Bourn, A. Skoufalos, E. H. Beck, and D. J. Castillo, "An innovative approach to health care delivery for patients with chronic conditions," *Population Health Management*, vol. 20, no. 1, pp. 23–30, Feb. 2017, doi: 10.1089/pop.2016.0076.

[4] N. Fares, R. S. Sherratt, and I. H. Elhajj, "Directing and orienting ICT healthcare solutions to address the needs of the aging population," Healthcare, vol. 9, no. 2, 147, Feb. 2021, doi: 10.3390/healthcare9020147.

[5] A.-M. Rahmani, N. K. Thanigaivelan, T. N. Gia, J. Granados, B. Negash, P. Liljeberg, and Hannu, "Smart e-health gateway: Bringing intelligence to internet-of-things based ubiquitous healthcare systems," in Proc. CCNC, Las Vegas, NV, USA, 2015, pp. 826–834, doi: 10.1109/CCNC.2015.7158084.

[6] I. Azimi, A. Anzanpour, A. M. Rahmani, T. Pahikkala, M. Levorato, P. Liljeberg, and N. Dutt, "HiCH: Hierarchical fog-assisted computing architecture for healthcare IoT," ACM Transactions on Embedded Computing Systems, vol. 16, no. 5s, 174, Oct. 2017, doi: 10.1145/3126501.

[7] L. Olsen, D. Aisner, and J. M. McGinnis (Eds.), "The learning healthcare system: Workshop summary," in Institute of Medicine (US) Roundtable on Evidence-Based Medicine, National Academies Press (US), 2017, doi: 10.17226/11903.

[8] T. M. Maddox, N. M. Albert, W. B. Borden, L. H. Curtis, T. B. Ferguson Jr., D. P. Kao, G. M. Marcus, E. D. Peterson, R. Redberg, J. S. Rumsfeld, N. D. Shah, J. E. Tcheng, and the American Heart Association Council on Quality of Care and Outcomes Research; Council on Cardiovascular Disease in the Young; Council on Clinical Cardiology; Council on Functional Genomics and Translational Biology; and Stroke Council, "The learning healthcare system and cardiovascular care: A scientific

statement from the American Heart Association," Circulation, vol. 135, no. 14, pp. 826–857, Mar. 2017, doi: 10.1161/CIR.0000000000000480.

[9] C. B. Forrest, F. D Chesley Jr., M. L. Tregear, and K. B. Mistry, "Development of the learning health system researcher core competencies," Health Services Research, vol. 53, no. 4, pp. 2615–2632, Aug. 2017, doi: 10.1111/1475-6773.12751.

[10] S. McLachlan, K. Dube, E. Kyrimi, N. Fenton, and the Health Informatics and Knowledge Engineering Research Group, "LAGOS: Learning health systems and how they can integrate with patient care," BMJ Health and Care Informatics, vol. 26, no. 1, e100037, 2019, doi: 10.1136/bmjhci-2019-100037.

[11] C. Friedman, J. Rubin, J. Brown, M. Buntin, M. Corn, L. Etheredge, C. Gunter, M. Musen, R. Platt, W. Stead, K. Sullivan, and D. Van Houweling, "Toward a science of learning systems: A research agenda for the high-functioning learning health system," J. American Medical Informatics Association, vol. 22, no. 1, pp. 43–50, Oct. 2014, doi: 10.1136/amiajnl-2014-002977.

[12] S. McLachlan, H. Potts, K. Dube, D. Buchanan, S. Lean, T. Gallagher, O. Johnson, B. Daley, W. Marsh, and N. Fenton, "The Heimdall framework for supporting characterisation of learning health systems," *BMJ Health and Care Informatics*, vol. 25, no. 2, pp. 77–87, 2018, doi: 10.14236/jhi.v25i2.996.

[13] J. Andreu-Perez, C. C. Y. Poon, R. D. Merrifield, S. T. C. Wong and G.-Z. Yang, "Big data for health," *IEEE J. Biom. Health Inform.*, vol. 19, no. 4, pp. 1193–1208, Jul. 2015, doi: 10.1109/JBHI.2015.2450362.

[14] P. Lambin, J. Zindler, B. G. L. Vanneste, L. VanDe Voorde, D. Eekers, I. Compter, K. M. Panth, J. Peerlings, R. T. H. M. Larue, T. M. Deist, A. Jochems, T. Lustberg, J. Soest, E. E. C. de Jong, A. J. G. Even, B. Reymen, N. Rekers, M. Gisbergen, E. Roelofs, S. Carvalho, R. T. H. Leijenaar, C. M. L. Zegers, M. Jacobs, J. Timmeren, P. Brouwers, J. A. Lal, L. Dubois, A. Yaromina, E. J. V. Limbergen, M. Berbee, W. van Elmpt, C. Oberije, B. Ramaekers, A. Dekker, L. J. Boersma, F. Hoebers, K. M. Smits, A. J. Berlanga, and S. Walsh, "Decision support systems for personalized and

participative radiation oncology," *Advanced Drug Delivery Reviews*, vol. 109, pp. 131–153, Jan. 2016, doi: 10.1016/j.addr.2016.01.006.

[15] G. W. Sledge Jr., R. S. Miller, and R. Hauser, "CancerLinQ and the future of cancer care," *American Society of Clinical Oncology Educational Book*, vol. 13, pp. 430–434, 2013, doi: 10.14694/EdBook_AM.2013.33.430.

[16] C. P. Friedman, A. K. Wong, and D. Blumenthal, "Achieving a nationwide learning health system," *Science Translational Medicine*, vol. 2, no. 57, p. 57cm29, Nov. 2010, doi: 10.1126/scitranslmed.3001456.

[17] S. R. Deeny and A. Steventon, "Making sense of the shadows: Priorities for creating a learning healthcare system based on routinely collected data," *BMJ Quality and Safety*, vol. 24, no. 8, pp. 505–515, Jun. 2015, doi: 10.1136/bmjqs-2015-004278B.

[18] T. J. Foley and L. Vale, "What role for learning health systems in quality improvement within healthcare providers?" *Learning Health Systems*, vol. 1, no. 4, e10025, May 2017, doi: 10.1002/lrh2.10025.

[19] S. McLachlan, K. Dube, O. Johnson, D. Buchanan, H. W. W. Potts, T. Gallagher, and N. Fenton, "A framework for analysing learning health systems: Are we removing the most impactful barriers?" *Learning Health Systems*, vol. 3, e10189, Mar. 2019, doi: 10.1002/lrh2.10189.

[20] L. Nguyen, E. Bellucci, and L. T. Nguyen, "Electronic health records implementation: An evaluation of information system impact and contingency factors," *Int. J. Medical Informatics*, vol. 83, no. 11, pp. 779–796, Nov. 2014, doi: 10.1016/j.ijmedinf.2014.06.011.

[21] R. Kaye, E. Kokia, V. Shalev, D. Idar, and D. Chinitz, "Barriers and success factors in health information technology: A practitioner's perspective," *J. Management & Marketing in Healthcare*, vol. 3, no. 2, pp. 163–175, Jul. 2013, doi: 10.1179/175330310X12736577732764.

[22] M. Lluch, "Healthcare professionals' organisational barriers to health information

technologies - a literature review," *Int. J. Medical Informatics*, vol. 80, no. 12, pp. 849–862, Dec. 2011, doi: 10.1016/j.ijmedinf.2011.09.005.

[23] J. King and B. Moulton, "Rethinking informed consent: The case for shared medical decision-making," *American J. Law & Medicine*, vol. 32, no. 4, pp. 429–501, Jan. 2021, doi: 10.1177/009885880603200401.

[24] M. Meingast, T. Roosta, and S. Sastry, "Security and privacy issues with health care information technology," in *Proc. IEMBS*, New York, NY, USA, 2006, pp. 5453–5458, doi: 10.1109/IEMBS.2006.260060.

[25] D. Alrahbi, M. Khan, and M Hussain, "Exploring the motivators of technology adoption in healthcare," *Int. J. Healthcare Management*, vol. 14, no. 1, pp. 50–63, May 2019, doi: 10.1080/20479700.2019.1607451.

[26] M. G. Weiner and P. J. Embi, "Toward reuse of clinical data for research and quality improvement: the end of the beginning?" *Annals of Internal Medicine, vol. 151, no. 5, pp. 359–360, Sep. 2009, doi: 10.7326/0003-4819-151-5-200909010-00141.*

[27] R. Amarasingham, R. E. Patzer, M. Huesch, N. Q. Nguyen, and B. Xie, "Implementing electronic health care predictive analytics: Considerations and challenges," *Health Affairs*, vol. 33, no. 7, pp. 1148–1154, Jul. 2014, doi: 10.1377/hlthaff.2014.0352.

[28] J. S. Brown, M. Kahn, and S. Toh, "Data quality assessment for comparative effectiveness research in distributed data networks," *Medical Care*, vol. 51, no. 8, pp. S22–S29, Aug. 2013, doi: 10.1097/MLR.0b013e31829b1e2c.

[29] Centers for Medicare & Medicaid Services', "Long-term care facility resident assessment instrument (RAI) user's manual," October 2019. [Online]. Available: https://downloads.cms.gov/files/mds-3.0-rai-manual-v1.17.1_october_2019.pdf

[30] F. Jiang, Y. Jiang, H. Zhi, Y. Dong, H. Li, S. Ma, Y. Wang, Q. Dong, H. Shen, Y. Wang, "Artificial intelligence in healthcare: Past, present and future," *Stroke and Vascular Neurology*, vol. 2, no. 4, e000101, Jun. 2017, doi: 10.1136/svn-2017-000101.

[31] R. E. Gliklich, N. A. Dreyer, and M. B. Leavy, *Registries for evaluating patient*

outcomes: A user's guide, Agency for Healthcare Research and Quality, Rockville, MD, USA, 3rd ed. [Online]. Available: https://www.ncbi.nlm.nih.gov/books/NBK208616.

[32] T. A. Sanborn, J. E. Tcheng, H. V. Anderson, C. E. Chambers, S. L. Cheatham, M. V. DeCaro, J. C. Durack, A. D. Everett, J. B. Gordon, W. E. Hammond, Z. M. Hijazi, V. S. Kashyap, M. Knudtson, M. J. Landzberg, M.A. Martinez-Rios, L. A. Riggs, K. H. Sim, D. J. Slotwiner, H. Solomon, W. Y. Szeto, B. H. Weiner, W. S. Weintraub, and J. R. Windle, "ACC/AHA/SCAI 2014 Health policy statement on structured reporting for the cardiac catheterization laboratory, a report of the American College of Cardiology clinical quality committee," *Circulation*, vol. 129, no. 24, pp. 2578–2609, Jun. 2014, doi: 10.1161/cir.0000000000000043.

[33] R. B. Zuckerman, S. H. Sheingold, E. J. Orav, J. Ruhter, and A. M. Epstein, "Readmissions, observation, and the hospital readmissions reduction program," *The New England J. Medicine*, vol. 374, no. 16, pp. 1543–1551, Apr. 2016, doi: 10.1056/NEJMsa1513024.

[34] J. M. Lillo-Castellano, I. Mora-Jiménez, R. Moreno-González, M. Montserrat-García-de-Pablo, A. García-Alberola and J. L. Rojo-Álvarez, "Big-data analytics for arrhythmia classification using data compression and kernel methods," in *Proc. CinC*, Nice, France, 2015, pp. 661–664, doi: 10.1109/CIC.2015.7410997.

[35] H. Huo and Y. Xu, "An elderly health care system using wireless sensor networks at home", in *Proc. SENSORCOMM*, Athens, Greece, 2009, pp. 158–163, doi: 10.1109/SENSORCOMM.2009.32.

[36] P. D. Kaur and I. Chana, "Cloud based intelligent system for delivering health care as a service," *Computer Methods and Programs in Biomedicine*, vol. 113, no. 1, pp. 346–359, Jan. 2014, doi: 10.1016/j.cmpb.2013.09.013.

[37] J. W. Kim, J. H. Lim, S. M. Moon, and B. Jang, "Collecting health lifelog data from smartwatch users in a privacy-preserving manner," *IEEE Trans. Consum. Electron.*, vol. 65, no. 3, pp. 369–378, Aug. 2019, doi: 10.1109/TCE.2019.2924466.

[38] S. Ivanov, D. Botvich, and S. Balasubramaniam, "Cooperative wireless sensor environments supporting body area networks," *IEEE Trans. Consum. Electron.*, vol. 58, no. 2, pp. 284–292, May 2012, doi: 10.1109/TCE.2012.6227425.

[39] H. Y. Tung, K. F. Tsang, H. C. Tung, K. T. Chui, and H. R. Chi, "The design of dual radio ZigBee homecare gateway for remote patient monitoring," *IEEE Trans. Consum. Electron.*, vol. 59, no. 4, pp. 756–764, Nov. 2013, doi: 10.1109/TCE.2013.6689686.

[40] P. P. Ray, N. Thapa, and D. Dash, "Implementation and performance analysis of interoperable and heterogeneous IoT-edge gateway for pervasive wellness care," *IEEE Trans. Consum. Electron.*, vol. 65, no. 4, pp. 464–473, Nov. 2019, doi: 10.1109/TCE.2019.2939494.

[41] D. Diaz-Sanchez, A. Marin, F. Almenarez, and A. Cortes, "Social applications in the home network," *IEEE Trans. Consum. Electron.*, vol. 56, no. 1, pp. 220–225, Feb. 2010, doi: 10.1109/TCE.2010.5439148.

[42] N. Dey, A. S. Ashour, F. Shi, S. J. Fong, and R. S. Sherratt, "Developing residential wireless sensor networks for ECG healthcare monitoring," *IEEE Trans. Consum. Electron.*, vol. 63, no. 4, pp. 442–449, Nov. 2017, doi: 10.1109/TCE.2017.015063.

[43] O. Fratu, C. Pena, R. Craciunescu, and S. Halunga, "Fog computing system for monitoring mild dementia and COPD patients - Romanian case study," in *Proc. TELSKS*, Nis, Serbia, 2015, pp. 123–128, doi: 10.1109/TELSKS.2015.7357752.

[44] M. Hartmann, U. S. Hashmi, and A. Imran, "Edge computing in smart health care systems: Review, challenges, and research directions," *Transactions on Emerging Telecommunications Technology*, vol. 33, no. 3, e3710, Aug. 2019, doi: 10.1002/ett.3710.

[45] C. H. Lee and H. J. Yoon, "Medical big data: promise and challenges," *Kidney Research and Clinical Practice*, vol. 36, no. 1, pp. 3–11, Mar. 2017, doi: 10.23876/j.krcp.2017.36.1.3.

[46] C.-H. Hung, Y.-W. Bai, and R.-Y. Tsai, "Design of blood pressure measurement with

a health management system for the aged," *IEEE Trans. Consum. Electron.*, vol. 58, no. 2, pp. 619–625, May 2012, doi: 10.1109/TCE.2012.6227468.

[47] J. Wang, Z. Zhang, B. Li, S. Lee, and R. S. Sherratt, "An enhanced fall detection system for elderly person monitoring using consumer home networks," *IEEE Trans. Consum. Electron.*, vol. 60, no. 1, pp. 23–29, Feb. 2014, doi: 10.1109/TCE.2014.6780921.

[48] H. Yan, H. Huo, Y. Xu, and M. Gidlund, "Wireless sensor network-based e-health system - implementation and experimental results," *IEEE Trans. Consum. Electron.*, vol. 56, no. 4, pp. 2288–2295, Nov. 2010, doi: 10.1109/TCE.2010.5681102.

[49] H. A. Al Hamid, S. M. M. Rahman, M. S. Hossain, A. Almogren, and A. Alamri, "A security model for preserving the privacy of medical big data in a healthcare cloud using a fog computing facility with pairing-based cryptography," *IEEE Access*, vol. 5, pp. 22313–22328, Sep. 2017, doi: 10.1109/ACCESS.2017.2757844.

[50] C. Guo, G. Lu, H. J. Wang, S. Yang, C. Kong, P. Sun, W. Wu, and Y. Zhang, "Secondnet: A data center network virtualization architecture with bandwidth guarantees," in *Proc. Co-NEXT*, Philadelphia, PA, USA, 2010, pp. 1–12, doi: 10.1145/1921168.1921188.

[51] D. Sarabia-Jácome, R.l Usach, C. E. Palau, and M. Esteve, "Highly-efficient fog-based deep learning AAL fall detection system," *Internet of Things*, vol. 11, 100185, Sep. 2020, doi: 10.1016/j.iot.2020.100185.

[52] A. P. Miettinen and J. K. Nurminen, "Energy efficiency of mobile clients in cloud computing," in *Proc. HotCloud*, Boston, MA, USA, 2010. [Online]. Available: https://www.usenix.org/conference/hotcloud-10/energy-efficiency-mobile-clients-cloud-computing.

[53] W. Yu, F. Liang, X. He, W. G. Hatcher, C. Lu, J. Lin, and X. Yang, "A survey on the edge computing for the internet of things," *IEEE Access*, vol. 6, pp. 6900–6919, Nov. 2017, doi: 10.1109/ACCESS.2017.2778504.

[54] R. Hu, H. Pham, P. Buluschek, and D. Gatica-Perez, “Elderly people living alone: Detecting home visits with ambient and wearable sensing,” in *Proc. MMHealth*, Mountain View, CA, USA, 2017, pp. 85–88, doi: 10.1145/3132635.3132649.

[55] Y. Cao, P. Hou, D. Brown, J. Wang, and S. Chen, “Distributed analytics and edge intelligence: Pervasive health monitoring at the era of fog computing,” in *Proc. Mobidata*, Hangzhou, China, 2015, pp. 43–48, doi: 10.1145/2757384.2757398.

[56] E. I. Gaura, J. Brusey, M. Allen, R. Wilkins, D. Goldsmith, and R. Rednic, “Edge mining the internet of things,” *IEEE Sensors J.*, vol. 3, no. 10, pp. 3816–3825, Oct. 2013, doi: 10.1109/JSEN.2013.2266895.

[57] S.-Y. Lee, P.-W. Huang, M.-C. Liang, J.-H. Hong, and J.-Y. Chen, “Development of an arrhythmia monitoring system and human study,” *IEEE Trans. Consum. Electron.*, vol. 64, no. 4, pp. 442–451, Nov. 2018, doi: 10.1109/TCE.2018.2875799.

[58] H. Wang, J. Gong, Y. Zhuang, H. Shen, and J. Lach, “HealthEdge: Task scheduling for edge computing with health emergency and human behavior consideration in smart homes,” in *Proc. BigData*, Boston, MA, USA, 2017, pp. 34–42, doi: 10.1109/BigData.2017.8258047.

[59] A. Alrawais, A. Alhothaily, C. Hu, and X. Cheng, “Fog computing for the internet of things: Security and privacy issues,” *IEEE Internet Comput.*, vol. 21, no. 2, pp. 34–42, Mar.-Apr. 2017, doi: 10.1109/MIC.2017.37.

[60] L. Rachakonda, S. P. Mohanty, E. Kougianos, and P. Sundaravadivel, “Stress-lysis: A DNN-integrated edge device for stress level detection in the IoMT,” *IEEE Trans. Consum. Electron.*, vol. 65, no. 4, pp. 474–483, Nov. 2019, doi: 10.1109/TCE.2019.2940472.

[61] L. Rachakonda, S. P. Mohanty, and E. Kougianos, “ilog: An intelligent device for automatic food intake monitoring and stress detection in the IoMT,” *IEEE Trans. Consum. Electron.*, vol. 66, no. 2, pp. 115–124, May 2020, doi: 10.1109/TCE.2020.2976006.

[62] C. Mouradian, D. Naboulsi, S. Yangui, R. H. Glitho, M. J. Morrow, and P. Polakos, "A comprehensive survey on fog computing: State-of-the-art and research challenges," *IEEE Commun. Surveys Tuts.*, vol. 20, no. 1, pp. 416–464, Nov. 2017, doi: 10.1109/COMST.2017.2771153.

[63] I. M. Ibrahim and A. M. Abdulazeez, "The role of machine learning algorithms for diagnosing diseases," *J. Applied Science and Technology Trends*, vol. 2, no. 1, pp. 10–19, Mar. 2021, doi: 10.38094/jastt20179.

[64] A. M. Joshi, P. Jain, S. P. Mohanty, and N. Agrawal, "iGLU 2.0: A new wearable for accurate non-invasive continuous serum glucose measurement in IoMT framework," *IEEE Trans. Consum. Electron.*, vol. 66, no. 4, pp. 327–335, Nov. 2020, doi: 10.1109/TCE.2020.3011966.

[65] D. Tomar, "A survey on data mining approaches for healthcare," *Int. J. Bio-Science and Bio-Technology*, vol. 5, no. 5, pp. 241–266, 2013, doi: 10.14257/ijbsbt.2013.5.5.25.

[66] S. Grampurohit and C. Sagarnal, "Disease prediction using machine learning algorithms," in *Proc. INCET*, Belgaum, India, 2020, doi: 10.1109/INCET49848.2020.9154130.

[67] S. Raj and K. C. Ray, "A personalized point-of-care platform for real-time ECG monitoring," *IEEE Trans. Consum. Electron.*, vol. 64, no. 4, pp. 452–460, Nov. 2018, doi: 10.1109/TCE.2018.2877481.

[68] C. Venkatesan, P. Karthigaikumar, A. Paul, S. Satheeskumaran, and R. Kumar, "ECG signal preprocessing and SVM classifier-based abnormality detection in remote healthcare applications," *IEEE Access*, vol. 6, pp. 9767–9773, Jan. 2018, doi: 10.1109/ACCESS.2018.2794346.

[69] S.-W. Fei, "Diagnostic study on arrhythmia cordis based on particle swarm optimization-based support vector machine," *Expert Systems with Applications*, vol. 37, no. 10, pp. 6748–6752, Oct. 2010, doi: 10.1016/j.eswa.2010.02.126.

[70] P. T. Seint, T. T. Zin, and M. Yokota, "Medication and meal intake monitoring using human-object interaction," in *Proc GCCE*, Nara, Japan, 2018, pp. 399–400, doi: 10.1109/GCCE.2018.8574854.

[71] R. R. Zebari, A. M. Abdulazeez, D. Q. Zeebaree, D. A. Zebari, and J. N. Saeed, "A comprehensive review of dimensionality reduction techniques for feature selection and feature extraction," *J. Applied Science and Technology Trends*, vol. 1, no. 2, pp. 56–70, May 2020, doi: 10.38094/jastt1224.

[72] A. Kalatzis, B. Mortazavi, and M. Pourhomayoun, "Interactive dimensionality reduction for improving patient adherence in remote health monitoring," in *Proc. CSCI*, Las Vegas, NV, USA, 2018, pp. 748–751, doi: 10.1109/CSCI46756.2018.00149.

[73] S. Dhiviya, A. Sariga, and P. Sujatha, "Survey on WSN using clustering," in *Proc. ICRTCCM*, Tindivanam, India, 2017, pp. 121–125, doi: 10.1109/ICRTCCM.2017.87.

[74] S. Ma, X. Zhang, C. Jia, Z. Zhao, S. Wang, and S. Wang, "Image and video compression with neural networks: A review," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 30, no. 6, pp. 1683-1698, Jun. 2020, doi: 10.1109/TCSVT.2019.2910119.

[75] J. Ding and Y. Wang, "A WiFi-based smart home fall detection system using recurrent neural network," *IEEE Trans. Consum. Electron.*, vol. 66, no. 4, pp. 308–317, Nov. 2020, doi: 10.1109/TCE.2020.3021398.

[76] S. Jayatilake and G. U. Ganegoda, "Involvement of machine learning tools in healthcare decision making," *J. Healthcare Engineering*, vol. 2021, 6679512, Jan. 2021, doi: 10.1155/2021/6679512.

[77] S. Liaqat, K. Dashtipour, S. A. Shah, A. Rizwan, A. A. Alotaibi, T. Althobaiti, K. Arshad, K. Assaleh, and N. Ramzan, "Novel ensemble algorithm for multiple activity recognition in elderly people exploiting ubiquitous sensing devices," *IEEE Sensors J.*, vol. 21, no. 16, pp. 18214–18221, Aug. 2021, doi: 10.1109/JSEN.2021.3085362.

[78] R. Lopes, A. Ayache, N. Makni, P. Puech, A. Villers, S. Mordon, and N. Betrouni,

"Prostate cancer characterization on MR images using fractal features," *Medical Physics*, vol. 38, no. 1, pp. 83–95, Dec. 2010, doi: 10.1118/1.3521470.

[79] K. Park, J. Park, and J. Lee, "An IoT system for remote monitoring of patients at home," *Applied Sciences*, vol. 7, no. 3, 260, Mar. 2017, doi: 10.3390/app7030260.

[80] X. Zhou, W. Liang, K. I.-K. Wang, H. Wang, L. T. Yang, and Q. Jin, "Deep-learning-enhanced human activity recognition for internet of healthcare things," *IEEE Internet of Things J.*, vol. 7, no. 7, pp. 6429–6438, Jul. 2020, doi: 10.1109/JIOT.2020.2985082.

[81] P. Jha, T. Biswas, U. Sagar, and K. Ahuja, "Prediction with ML paradigm in healthcare System," in *Proc. ICESC*, Coimbatore, India, 2021, pp. 1334–1342, doi: 10.1109/ICESC51422.2021.9532752.

[82] A. Site, J. Nurmi, and E. S. Lohan, "Systematic review on machine-learning algorithms used in wearable-based ehealth data analysis," *IEEE Access*, vol. 9, pp. 112221–112235, Aug. 2021, doi: 10.1109/ACCESS.2021.3103268.

Chapter 5: Requirements for Adaptive Consumer Gateways in Residential Learning Healthcare Systems

This chapter is part of a position paper that has been published in IEEE Transactions on Consumer Electronics Journal with the title: “Requirements for Adaptive Consumer Gateways in Residential Learning Healthcare Systems: Bringing Intelligence to the Edge”.

N. Fares and R. S. Sherratt, "Requirements for Adaptive Consumer Gateways in Residential Learning Healthcare Systems: Bringing Intelligence to the Edge," in IEEE Transactions on Consumer Electronics, doi: 10.1109/TCE.2023.3326570.

A gateway is a key component in residential healthcare systems. Enabling adaptability and applying intelligence to the gateway will promote residential healthcare systems to become Learning Healthcare Systems (LHSs) that can perform real-time decision making locally at the edge. This leads to the exciting potential of a new research field in patient/consumer-oriented gateways and consumer products that can adapt to different scenarios based on the patient’s/consumer’s healthcare needs and can learn about the patient/consumer, and over time can adapt accordingly. While patient/consumer healthcare gateways exist, they tend to be fixed to specific medical conditions, and are not upgradeable or adaptive. To be able to develop the introduced adaptive consumer gateway for patient/consumer healthcare applications, this chapter identifies a set of requirements concerning scalability, energy efficiency, reliability, availability, interoperability, and privacy that needs to be fulfilled before any product or service can be created. Intervention in local data processing, local data storage, embedded data mining, security, interoperability, and configurability that could serve the development process are also discussed. This chapter provides the requirements for the innovation of a one-for-all smart adaptive patient/consumer gateway in residential learning healthcare systems and to influence the patient/consumer healthcare field to consider the benefits of moving to adaptive gateways for future developments.

In this chapter we propose a set of requirements for the development of adaptive gateways for residential LHSs that enhance the patient/consumer healthcare experience. The gateway is to be located at the edge, at the patient's/consumers' premises. The smartness and adaptability of the proposed gateway requirements lays in extending the roles of the gateway to include several characteristics as local data processing, local data storage, embedded data mining, local decision making, security, interoperability and reconfigurability.

The adaptive gateway to be developed needs to consist of a data phase, knowledge phase, and evaluation phase as shown in ***Figure 5.1***. After the execution of the three phases the initial phase commences once more, where in each phase current best practices coupled with the latest scientific understanding are used to optimize the process.

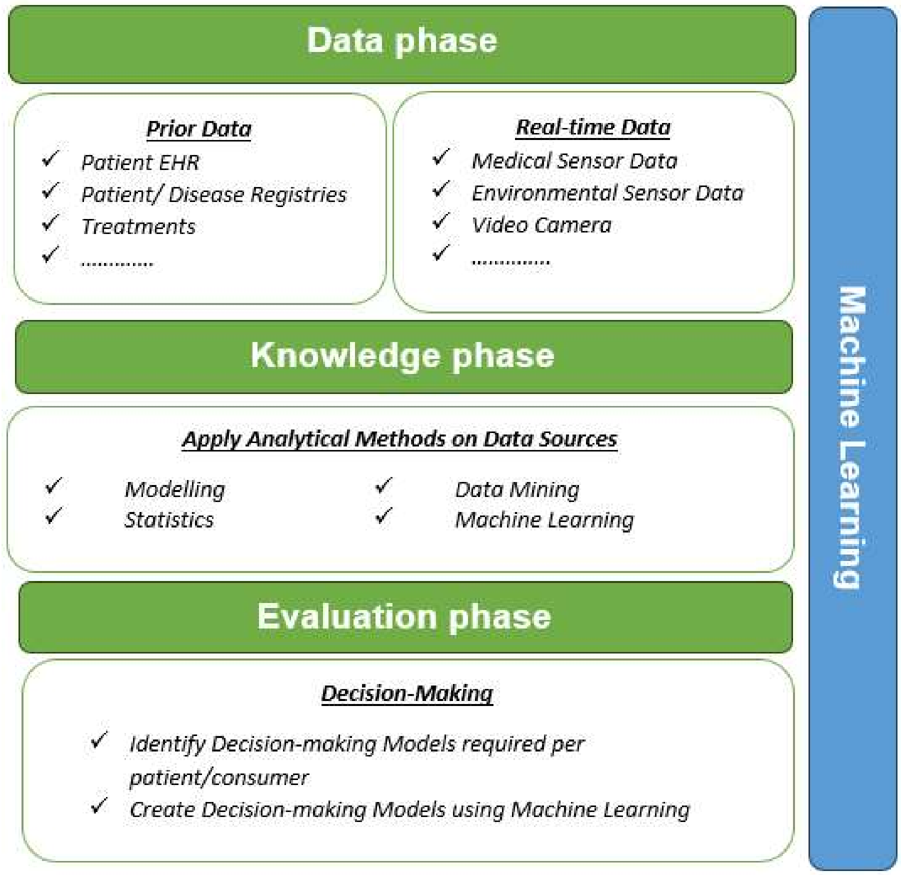

Figure 5.1: Overview of LHS phases

The ***data phase*** handles the attainment and mining of prior data and real-time data collected from a variety of data sources such as EHR, EMR, and sensor data using ML algorithms. In this phase, data from different data sources are integrated and classified with the aim of addressing acute and chronic diseases. To ensure quality of data sources there is a need to adopt Heimdall's LHS taxonomy and framework [1] that focuses on individual patients and brings systematized PM solutions. Thus, a patient/consumer healthcare specific model must be set up based on accessible clinical database data as EHR data appraised with sensor data collected from the consumer's living environment. At this phase data mining of the data sources is performed at the edge by applying ML algorithms. First, there is a need to identify the data mining model to be used. Descriptive data mining models are mainly used for classification, clustering, association rules, and correlation analysis of datasets. While predictive data mining models are used for classification, regression, and categorization of datasets [2]. Unfortunately, there is no single-best algorithm for every dataset, including biomedical datasets [3]. Thus, it is critical to know which algorithms provide greater accuracy on the dataset provided. Classification algorithms as SVM are widely used in data mining due to their prediction power but there is a need to carefully use noise reduction approaches as feature selection methods to avoid missing important relationships between different variables. Clustering algorithms are widely used when very little information about data is available as in the study of genes. And it's shown in research that the k-means algorithm provides the best clustering accuracy and is very scalable and efficient [3]. But it is best to be used with numerical data since clustering algorithms have problems in the conversion from categorical to numerical data [3].

The ***knowledge phase*** is responsible for performing sophisticated analytical methods as data mining and machine learning on the aggregated, classified, or categorized data to harness the knowledge concluded for the detection, prediction, and monitoring of chronic diseases, aspects of health deterioration, and dangerous physical situations [4, 5].

The ***evaluation phase*** is responsible for decision making. In this phase, suitable ML algorithms that showed promising results in analyzing different features in mined data such as SVM, neural networks, and deep learning for decision making based on the outcomes of the knowledge phase are implemented based on the patient's /consumer's healthcare requirements. SVM and neural networks in combination with ensemble algorithms showed superior results in decision making scenarios [6]. Therefore, a hybrid data mining model needs to be designed and implemented at the gateway to obtain higher accuracy throughout its three phases of data mining including tasks starting from dimensionality reduction to decision making [3].

The purpose behind the use of edge computing is to benefit from low latency, high coverage, better reliability than cloud-based models, lower energy consumption, and higher level of security and privacy, although in many cases data quality and availability are affected by the need to protect consumers' confidentiality.

Following these requirements in the implementation of smart edge based adaptive gateways enables the production of a unified system that could be mass market due to its adaptability, flexibility, cost efficiency, and availability.

- Adaptability is achieved through the ability to modify the choice of collected data and the analysis process based on the changing need of the consumer with time choosing from a variety of ML algorithms preset in the system.

- Flexibility is attained by the capability of modifying the analysis process target between monitoring, detection, and prediction of medical conditions as well as the ability to merge between these targets based on the differing needs of every patient/consumer.

- The cost efficiency of the proposed system lays in its unified nature that allows its adaptation based on the needs of each patient/consumer.

- Availability is achieved by setting the gateway at the premises of the consumer making the analysis and the decision-making process locally independent of internet availability.

To fulfill the requirements presented for a smart adaptive gateway for LHSs, there is a need to address emerging challenges and providing possible solutions as identifying the best choice of architecture, enabling technology, security and privacy, protocols, networks, physical systems, and possible applications.

- The adaptive gateway at the edge must be developed using a Service Oriented Architecture (SOA) that permits various devices in the system to perform independently, where different operations are properly defined and altered without degrading the interoperability of the system [7, 8].

- For network availability different communication technologies may be used for short range communication such as RFID, Wi-Fi, Zigbee, Bluetooth [9]. Zigbee outperformed the other technologies since it includes a processing center responsible for data analysis and aggregation, and ensures low power consumption, high transmission rate, and high network capacity [10]. As for long distance communication, the Internet is considered the external channel.

- For security and privacy attainment, blockchain technology can be deployed to solve the problem of data fragmentation, ensures secure and protective sharing of sensitive medical information, and increases transparency between doctors and patients. Blockchain technology follows the agreement rules and data exchange policies with a smart contract mechanism to access different EMRs that are stored in the blockchain [10]. Healthcare Data Gateway (HDG) is an application that uses blockchain technology and provides authority to patients to share their information. Herein, the consumer can control and share their information without violating the privacy policy [11]. MQTT communication protocol is a strong candidate for many healthcare scenarios. It provides solutions to attain a scalable, interoperable, secure IoT architecture in combination with security protocols like TLS/SSL for data encryption and authentication [12].

- As for power consumption lately, researchers are trying to design healthcare devices that can generate power for themselves by the integration of the IoT system with renewable energy systems [10].

- Real-time monitoring in LHSs can be possible throughout the integration of nanoelectronics, big data, and IoT [13].

- For local-edge analytics and decision making to be achieved there is a need to shift reasoning towards the edge using software such as TinyML and hardware such as Tensor processing units with the aim of combining hardware and software to enable ML models and DL algorithms on compact, relatively cheap, and power-efficient devices [14, 15].

From the results of our research, ***Table 5.1*** presents a compiled list of requirements for the development of residential LHS with relevant references and a textual description for each requirement. The requirements in the table are categorized into architectural, data sources, and gateway requirements. Such requirements were not previously known and need to be defined for the development of LHS systems in the future.

TABLE 5.1
LIST OF REQUIREMENTS FOR RESIDENTIAL LHS

Requirement	Reference	Description
A. Requirements for LHS architecture		
Apply sequential phases	Lambin et al. [16].	Data collection phase, knowledge phase, application phase, and evaluation phase.
Adopt Heimdall taxonomy and framework	McLachlan et al. [1], McLachlan et al. [17].	To improve the focus on the individual consumer's health.
B. Requirements for Data Sources		
Develop an optimal EHR user interface.	Brown et al. [18], CM&MS [19].	To improve the consistency of data entry and decrease the amount of unstructured, uninterpretable data in the EHR.
Use ML algorithms to Structure and remodel the available EHR data.	Jiang et al. [20].	To enable different forms of feature extraction as simple concept, temporal, and relation extraction features.
Apply ML algorithms on sensor data at different stages.	Lillo-Castellano et al. [6].	ML algorithms for data compression, data mining, data analysis, and decision making.
C. Requirements for Smart Adaptive Gateways		
Develop an Edge-based computing gateway.	Hartmann et al. [21], Sarabia-Jácome et al. [22], Miettinen et al. [23], Yu et al. [24] Hu et al. [25], Cao et al. [26].	To fulfill requirements as reduced latency in time-dependent solutions, energy efficiency, higher level of security and privacy, accurate location awareness, and easier usability.
Merge cloud-based and fog-based computing.	Friedman et al. [27].	To overcome the architectural limitations of both computing systems.
Scalable.	Alrawais et al. [28], Rachakonda et al. [29], Mouradian et al. [30].	Can select from or configure data sources to be used and identify analytical methods to be applied choosing from a variety of ML algorithms preset in the system.
Consumer Oriented.	Lee et al. [31].	Capable of modifying the analysis process target between monitoring, detection, and prediction of medical conditions as well as the ability to merge between these targets based on the differing needs of every consumer
Cost-efficient.	Hartmann et al. [21], Alrawais et al. [28], Zebari et al. [32].	Has a unified nature that allows its adaptation based on the needs of each consumer.
Has a Service Oriented Architecture (SOA).	Kim et al. [7], Avila et al. [8].	Permits various devices in the system to perform independently without degrading the interoperability of the system.
Ensures network availability at the edge.	Ghamari et al. [9].	Use short range communication technologies as RFID, Wi-Fi, Zigbee, and Bluetooth at the edge.
Ensures security and privacy.	Pradhan et al. [10], Yue et al. [11].	Deploy blockchain technologies to ensures secure and protective sharing of sensitive medical information over the network.

References

[1] S. McLachlan, H. Potts, K. Dube, D. Buchanan, S. Lean, T. Gallagher, O. Johnson, B. Daley, W. Marsh, and N. Fenton, “The Heimdall framework for supporting characterisation of learning health systems,” *BMJ Health and Care Informatics*, vol. 25, no. 2, pp. 77–87, 2018, doi: 10.14236/jhi.v25i2.996.

[2] N. Jothi, N. A. Rashid, and W. Husain, “Data mining in healthcare – a review,” Procedia Computer Science, vol. 72, pp. 306–313, 2015, doi: 10.1016/j.procs.2015.12.145.

[3] I. Yoo, P. Alafaireet, M. Marinov, K. Pena-Hernandez, R. Gopidi, J.-F. Chang, and L. Hua, “Data mining in healthcare and biomedicine: A survey of the literature,” *J. Medical Systems,* vol. 36, pp. 2431–2448, 2012, doi: 10.1007/s10916-011-9710-5.

[4] P. Jha, T. Biswas, U. Sagar, and K. Ahuja, “Prediction with ML paradigm in healthcare System,” in *Proc. ICESC*, Coimbatore, India, 2021, pp. 1334–1342, doi: 10.1109/ICESC51422.2021.9532752.

[5] A. Site, J. Nurmi, and E. S. Lohan, “Systematic review on machine-learning algorithms used in wearable-based ehealth data analysis,” IEEE Access, vol. 9, pp. 112221–112235, Aug. 2021, doi: 10.1109/ACCESS.2021.3103268.

[6] J. M. Lillo-Castellano, I. Mora-Jiménez, R. Moreno-González, M. Montserrat-García-de-Pablo, A. García-Alberola and J. L. Rojo-Álvarez, “Big-data analytics for arrhythmia classification using data compression and kernel methods,” in Proc. CinC, Nice, France, 2015, pp. 661–664, doi: 10.1109/CIC.2015.7410997.

[7] J. W. Kim, J. H. Lim, S. M. Moon, and B. Jang, “Collecting health lifelog data from smartwatch users in a privacy-preserving manner,” IEEE Trans. Consum. Electron., vol. 65, no. 3, pp. 369–378, Aug. 2019, doi: 10.1109/TCE.2019.2924466.

[8] K. Avila, P. Sanmartin, D. Jabba, M. Jimeno, “Applications based on service-oriented architecture (SOA) in the field of home healthcare,” Sensors, vol. 17, no. 8, 1703, Jul. 2017, doi: 10.3390/s17081703.

[9] M. Ghamari, B. Janko, R. Sherratt, W. Harwin, R. Piechockic, and C. Soltanpur, “A Survey on wireless body area networks for ehealthcare systems in residential environments,” Sensors, vol. 16, no. 6, 831, Jun. 2016, doi: 10.3390/s16060831.

[10] B. Pradhan, S. Bhattacharyya, and K. Pal, “IoT-based applications in healthcare devices,” J. Healthcare Engineering, vol. 2021, 6632599, Mar. 2021, doi: 10.1155/2021/6632599.

[11] X. Yue, H. Wang, D. Jin, M. Li, and W. Jiang, “Healthcare data gateways: Found healthcare intelligence on blockchain with novel privacy risk control,” J. Medical Systems, vol. 40, 218, Oct. 2016, doi: 10.1007/s10916-016-0574-6.

[12] P. Desai, A. Sheth and P. Anantharam, "Semantic Gateway as a Service Architecture for IoT Interoperability," 2015 IEEE International Conference on Mobile Services, New York, NY, USA, 2015, pp. 313-319, doi: 10.1109/MobServ.2015.51.

[13] M. Bansal and B. Gandhi, “IoT & big data in smart healthcare (ECG monitoring),” in Proc. COMITCon, Faridabad, India, 2019, pp. 390–396, doi: 10.1109/COMITCon.2019.8862197.

[14] H. K. Bharadwaj, A. Agarwal, V. Chamola, N. R. Lakkaniga, V. Hassija, M. Guizani, and B. Sikdar, “A review on the role of machine learning in enabling IoT based healthcare applications,” IEEE Access, vol. 9, pp. 38859–38890, Feb. 2021, doi: 10.1109/ACCESS.2021.3059858.

[15] V. Tsoukas, E. Boumpa, G. Giannakas, and A. Kakarountas, “A review of machine learning and TinyML in healthcare,” in Proc. PCI, Volos, Greece, 2021, doi: 10.1145/3503823.3503836.

[16] P. Lambin, J. Zindler, B. G. L. Vanneste, L. VanDe Voorde, D. Eekers, I. Compter, K. M. Panth, J. Peerlings, R. T. H. M. Larue, T. M. Deist, A. Jochems, T. Lustberg, J. Soest, E. E. C. de Jong, A. J. G. Even, B. Reymen, N. Rekers, M. Gisbergen, E. Roelofs, S. Carvalho, R. T. H. Leijenaar, C. M. L. Zegers, M. Jacobs, J. Timmeren, P. Brouwers, J. A. Lal, L. Dubois, A. Yaromina, E. J. V. Limbergen, M. Berbee, W. van Elmpt, C. Oberije, B. Ramaekers, A. Dekker, L. J. Boersma, F. Hoebers, K. M. Smits, A. J. Berlanga, and S. Walsh, “Decision support systems for personalized and participative radiation oncology,” Advanced Drug Delivery Reviews, vol. 109, pp. 131–153, Jan. 2016, doi: 10.1016/j.addr.2016.01.006.

[17] S. McLachlan, K. Dube, E. Kyrimi, N. Fenton, and the Health Informatics and Knowledge Engineering Research Group, “LAGOS: Learning health systems and how they can integrate with patient care,” BMJ Health and Care Informatics, vol. 26, no. 1, e100037, 2019, doi: 10.1136/bmjhci-2019-100037.

[18] J. S. Brown, M. Kahn, and S. Toh, “Data quality assessment for comparative effectiveness research in distributed data networks,” Medical Care, vol. 51, no. 8, pp. S22–S29, Aug. 2013, doi: 10.1097/MLR.0b013e31829b1e2c.

[19] Centers for Medicare & Medicaid Services’, “Long-term care facility resident assessment instrument (RAI) user’s manual,” October 2019. [Online]. Available: https://downloads.cms.gov/files/mds-3.0-rai-manual-v1.17.1_october_2019.pdf

[20] F. Jiang, Y. Jiang, H. Zhi, Y. Dong, H. Li, S. Ma, Y. Wang, Q. Dong, H. Shen, Y. Wang, "Artificial intelligence in healthcare: Past, present and future," Stroke and Vascular Neurology, vol. 2, no. 4, e000101, Jun. 2017, doi: 10.1136/svn-2017-000101.

[21] M. Hartmann, U. S. Hashmi, and A. Imran, "Edge computing in smart health care systems: Review, challenges, and research directions," Transactions on Emerging Telecommunications Technology, vol. 33, no. 3, e3710, Aug. 2019, doi: 10.1002/ett.3710.

[22] D. Sarabia-Jácome, R.l Usach, C. E. Palau, and M. Esteve, "Highly-efficient fog-based deep learning AAL fall detection system," Internet of Things, vol. 11, 100185, Sep. 2020, doi: 10.1016/j.iot.2020.100185.

[23] A. P. Miettinen and J. K. Nurminen, "Energy efficiency of mobile clients in cloud computing," in Proc. HotCloud, Boston, MA, USA, 2010. [Online]. Available: https://www.usenix.org/conference/hotcloud-10/energy-efficiency-mobile-clients-cloud-computing.

[24] W. Yu, F. Liang, X. He, W. G. Hatcher, C. Lu, J. Lin, and X. Yang, "A survey on the edge computing for the internet of things," IEEE Access, vol. 6, pp. 6900–6919, Nov. 2017, doi: 10.1109/ACCESS.2017.2778504.

[25] R. Hu, H. Pham, P. Buluschek, and D. Gatica-Perez, "Elderly people living alone: Detecting home visits with ambient and wearable sensing," in Proc. MMHealth, Mountain View, CA, USA, 2017, pp. 85–88, doi: 10.1145/3132635.3132649.

[26] Y. Cao, P. Hou, D. Brown, J. Wang, and S. Chen, "Distributed analytics and edge intelligence: Pervasive health monitoring at the era of fog computing," in Proc. Mobidata, Hangzhou, China, 2015, pp. 43–48, doi: 10.1145/2757384.2757398.

[27] C. P. Friedman, A. K. Wong, and D. Blumenthal, "Achieving a nationwide learning health system," Science Translational Medicine, vol. 2, no. 57, p. 57cm29, Nov. 2010, doi: 10.1126/scitranslmed.3001456.

[28] A. Alrawais, A. Alhothaily, C. Hu, and X. Cheng, "Fog computing for the internet of things: Security and privacy issues," IEEE Internet Comput., vol. 21, no. 2, pp. 34–42, Mar.-Apr. 2017, doi: 10.1109/MIC.2017.37.

[29] L. Rachakonda, S. P. Mohanty, E. Kougianos, and P. Sundaravadivel, "Stress-lysis: A DNN-integrated edge device for stress level detection in the IoMT," IEEE Trans. Consum. Electron., vol. 65, no. 4, pp. 474–483, Nov. 2019, doi: 10.1109/TCE.2019.2940472.

[30] C. Mouradian, D. Naboulsi, S. Yangui, R. H. Glitho, M. J. Morrow, and P. Polakos, "A comprehensive survey on fog computing: State-of-the-art and research

challenges," IEEE Commun. Surveys Tuts., vol. 20, no. 1, pp. 416–464, Nov. 2017, doi: 10.1109/COMST.2017.2771153.

[31] S.-Y. Lee, P.-W. Huang, M.-C. Liang, J.-H. Hong, and J.-Y. Chen, "Development of an arrhythmia monitoring system and human study," IEEE Trans. Consum. Electron., vol. 64, no. 4, pp. 442–451, Nov. 2018, doi: 10.1109/TCE.2018.2875799.

[32] R. R. Zebari, A. M. Abdulazeez, D. Q. Zeebaree, D. A. Zebari, and J. N. Saeed, "A comprehensive review of dimensionality reduction techniques for feature selection and feature extraction," J. Applied Science and Technology Trends, vol. 1, no. 2, pp. 56–70, May 2020, doi: 10.38094/jastt1224.

Chapter 6: RLHS Architecture Design and Implementation

This chapter includes part of a position paper that has been published in IEEE Transactions on Consumer Electronics Journal with the title: "Requirements for Adaptive Consumer Gateways in Residential Learning Healthcare Systems: Bringing Intelligence to the Edge" in addition to a detailed explanation of the implementation process.

N. Fares and R. S. Sherratt, "Requirements for Adaptive Consumer Gateways in Residential Learning Healthcare Systems: Bringing Intelligence to the Edge," in IEEE Transactions on Consumer Electronics, doi: 10.1109/TCE.2023.3326570.

"A learning healthcare system is one that is designed to generate and apply the best evidence for the collaborative healthcare choices of each patient and provider; to drive the process of discovery as a natural outgrowth of patient care; and to ensure innovation, quality, safety, and value in healthcare" [1]. The proposed concept of Residential Learning Healthcare System puts major emphasis on inclusion of patients into decision-making to personalize care plans instead of delivering a standard treatment for every individual meeting certain criterion. It also focuses on exploring the potential of data collected in patient's residence as a source of up-to-date patient-specific knowledge, which could be implemented into decision-making in a more agile manner than only using randomized healthcare data collected from electronic health records or clinical trials. A multidisciplinary literature review, according to chapter 2 and 3, enables a conceptual design of a RLHS that adapts to every patient's healthcare requirements and permits local decision making to enhance caregiving quality at the patient's residence.

6.1 RLHS Architecture Design

In this section, we present the architecture of the proposed Residential Learning Healthcare System as shown in ***Figure 6.1***. This architecture can be implemented in smart homes or caregiving centers where patients that require daily care reside. In such systems, patients/consumers are equipped with body-worn or implanted sensors to record health related information for personal monitoring of multiple parameters. Patient’s context information is also provided by contextual sensors that help in identifying unusual patterns and make more precise inferences about the situation. Other sensors and actuators can also be connected to the system to transmit data to medical staff as high-resolution images. The architecture of the proposed system consists of three main layers: Sensor nodes layer, Edge computing layer including a Consumer-oriented adaptive gateway, and a Cloud computing platform (Back-end).

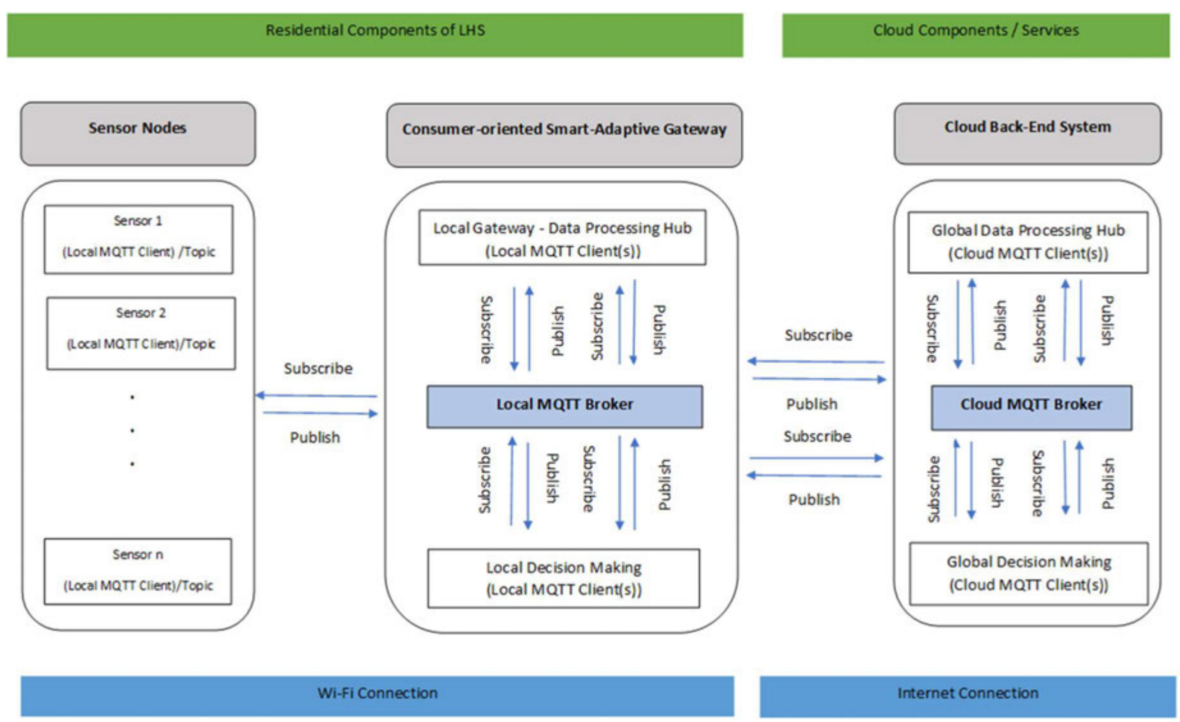

Figure 6.1: Residential Learning Healthcare System Architecture

Sensors in a sensor node can be based on different communication protocols such as Wi-Fi, Bluetooth Low Energy (BLE), and 6LoWPAN. Sensors are grouped based on their functionality. Environmental sensors communicate with other components of the system based on the microcontroller or microprocessor used and the communication protocols it supports such as SPI, BLE, Wi-Fi, and 6LoWPAN. Biomedical sensors are also connected to a microcontroller or a microprocessor, have a power managing unit, and a wireless communication chip that supports many-to-many communications. In our scenario sensor nodes and the adaptive gateway are connected to a local Area Network via Wi-Fi.

The Consumer-Oriented Adaptive Gateway layer consists of three components: a local gateway software responsible for local data handling, a local MQTT (Message Queuing Telemetry Transport) Broker responsible for the communication between different components of the residential LHS, and a decision-making component responsible for reporting results, giving feedback, and delivering notifications and alerts to the patient/consumer independent of internet connection availability.

The Cloud layer consists of a global data handling hub performing heavy computational tasks on the collected and stored data, a cloud based MQTT broker that allows communication with the local MQTT broker at consumer’s residence, and a decision-making model(s) supporting advanced machine learning algorithms for more powerful data analysis and decision making.

In this work we focused on demonstrating a set of requirements from the list of proposed requirements for residential LHS presented in chapter 5. We present a demonstration of an edge-based gateway that ensures network availability and flow of data at the edge independent of Internet availability, performs local decision making at the edge, adaptive and scalable in the sense of being capable to select the healthcare decision making models based on the patient’s/consumer’s changing needs with time, and merges edge and cloud-based computing for better decision making and analysis.

To ensure the flow of data between different components of residential LHS at the edge independent of Internet availability, a local MQTT Broker is set up. MQTT enables communication between different components of the system overcoming the gaps between hardware and software. All devices collaborate with a messaging flow publish and subscribe. Mosquitto, a lightweight open source MQTT broker was installed on a portable computer running linux at the patient's/consumer's residence performing as the smart-adaptive gateway at the edge (*PC1*). The local MQTT broker enables reliable communication, lower latency, and improved response time between different components of the system. MQTT empowers Edge computing by moving from sensor edge towards device Edge (IoT gateways) where the local gateway aggregates and process data from local sensors and make preliminary decisions locally independent of Internet availability and is as well connected to the cloud via Internet for detailed analysis and advanced decision making. The local gateway is connected to the cloud through bridging the local MQTT broker with another broker on the cloud. The local MQTT broker/server uses SSL/TLS (Secure Sockets Layer/Transport Layer Security) certificates to ensure secure connection and data transmission between MQTT clients (sensors, gateway, and other components) to solve the problem of IP broadcasting by being responsible for domain name discovery resolving.

To develop a consumer oriented residential LHS, the decision-making component should be designed and implemented targeting the specific needs of the patient/consumer. As a proof of concept, we created a heart disease prediction model trained and tested on a pre-collected heart disease occurrence possibility dataset. Based on the variables in the heart disease csv file, demos for 13 sensors were implemented on another portable computer at the consumer's residence (*PC2*). The sensors are connected to the local gateway through the local MQTT broker. The sensors, the local gateway, and the cloud end system are all MQTT clients subscribing/publishing to specific topics to share data. Client connections and their parameters are specified based on their functionality. The sensors publish messages to the local MQTT broker, across different topics based on the type of data being published. The local gateway subscribes to different topics through the local MQTT broker and publishes to the local decision-making model/models. It also publishes to other Clients on the Cloud MQTT broker network responsible for global data handling and decision making. Client instances are created for both the local MQTT broker and the MQTT broker hosted on the cloud. Multiple clients can be added based on the end user's requirements. To ensure scalability and interoperability of the introduced residential LHS, multiple machine learning models based on consumer's healthcare requirements can be added to the system as separate clients to perform any kind of data analysis locally or at the cloud as shown in *figure 6.1*. For every sensor connection that is being subscribed to by the local MQTT broker, an adjacent cloud connection is created to publish the received messages. Data received from different sensors was saved in queues in the local gateway. For each sensor, two queues are created to guarantee the same exact data in a specific time is sent to local broker and the cloud. One queue publishes data to the cloud while the other publishes to the local machine learning model.

6.2 RLHS Architecture Implementation

In this work, we have created various components of the RLHS system using the Python programming language. To demonstrate the feasibility of our research, we've generated experimental code, which is conveniently stored in a accessible directory labelled as "MQTT-RLHS."

6.2.1 Sensor Layer Implementation

The Sensor nodes layer can consist of different types of sensor networks such as environmental/ contextual sensors network, e-health / wearable sensors network, and video monitoring network. Sensors in a sensor node can be based on different communication protocols such as Wi-Fi, Bluetooth Low Energy (BLE), and 6LoWPAN [2]. Sensors are grouped based on their functionality in residential healthcare monitoring systems.

Contextual sensors used for collecting room temperature, humidity, air pressure and light levels, person's mobility within a room, and water flow can communicate with other components of the residential learning healthcare system based on the microcontroller or microprocessor used and the communication protocols it supports as SPI, BLE, Wi-Fi, and 6LoWPAN. E-health sensors as glucose sensor, body temperature sensor, motion sensor, and ECG analog front-end sensor are also connected to a microcontroller or a microprocessor, have a power managing unit, and a wireless communication chip that supports many-to-many communications. The video monitoring network / node can be used for tracking patients navigating their residence environment and providing continuous quantity of movement information. The camera needs to be connected to a processing unit that can operate several cameras in the residential healthcare system and can integrate video data in into a JSON string and the transmitted over MQTT protocol to other devices in the residential healthcare system [3]. To demonstrate the proposed RLHS architecture and implement the proposed system requirements, we focused on the design and implementation of the smart adaptive gateway component, assuming that sensor networks can be installed and implemented based on a previous work done by SPHERE project [4] that provides detailed information about sensors installation in smart homes. Thus, we created demo sensors as MQTT Clients in Python to be connected to the adaptive smart gateway using a Local MQTT Broker to prove our concept.

In the demonstration we performed, we focused on one healthcare requirement, heart disease monitoring and prediction, thus we created sensors based on a heart disease prediction csv file. We created 13 sensors using Python. The sensors are connected to the local gateway through mosquito, the local MQTT broker. The sensors publish messages to the local broker, and the local gateway receives sensor messages by subscribing to sensor topics. An example of Python code written to create a demo sensor is shown in the ***Python code box 6.1****: Sensor Code Sample* below.

Python code box 6.1: Sensor Code Sample

```
import paho.mqtt.client as mqtt
import time
import sys
import random

def on_log(client,userdata,level,buf):
   print("log: " + buf)

def on_connect(client,userdata,flags,rc):
   if rc==0:
      client.connected_flag=True
      print("connection successfull")
   else:
      print("Bad connection returned code= ",rc)
      client.bad_connection_flag=True
def on_disconnect(client,userdata,flags,rc=0):
   print("Disconnected result code "+str(rc))
   client.connected_flag=False
   client.disconnect_flag=True

def on_message(client,userdata,msg):
   topic=msg.topic
   m_decode=str(msg.payload.decode("utf-8","ignore"))
   print("message received :",m_decode)

def on_publish(client,userdata,result):
   print("publish successfull ",str(result),"\n")

broker="debian"
port=8883
client= mqtt.Client()
client.connected_flag=False
mqtt.Client.bad_connection_flag=False
client.on_connect=on_connect
client.on_disconnect=on_disconnect
#client.on_log=on_log
client.on_publish = on_publish
client.on_message=on_message
client.tls_set("C:/ MQTT-Sensor-main/Mosquitto Config/certs/ca.crt",
"C:/ MQTT-Sensor-main/Mosquitto Config/certs/client1.crt",
"C:/ MQTT-Sensor-main/Mosquitto Config/certs/client1.key"
)
print("connecting to broker",broker)

client.loop_start()
```

6.2.2 Smart adaptive gateway implementation

The smart adaptive gateway proposed in this work acts as the touching point between sensor networks and the Cloud services. To prove our concept of the proposed requirements for Residential Learning Healthcare Gateway discussed in chapter 5, we tried to implement a set of the main requirements of the RLHS smart and adaptive gateway. We worked on extending the role of the gateway to support several features as bringing intelligence to the edge by introducing local decision making at the gateway independent of Internet availability. We focused on developing a scalable gateway that enables adding new data sources and decision-making models based on the patient/consumer healthcare requirements. We designed the code of the proposed gateway to be service oriented in terms of isolating each service to perform independently without degrading the interoperability of the system.

6.2.2.1 Data Handling at gateway

Data handling at the Residential Learning healthcare gateway using MQTT with a local broker typically involves collecting, transmitting, and managing healthcare-related data from various medical devices and sensors. The MQTT local broker provides an efficient and scalable solution for data handling in RLHS, ensuring real-time communication, data integrity, and security for critical healthcare data.

Processing sensor data at a local healthcare gateway using queues through an MQTT local broker involves efficiently managing and handling the data generated by various sensors within the RLHS. Using queues in conjunction with MQTT helps ensure that data is processed in an orderly and efficient manner, particularly when dealing with large volumes of data or when you need to decouple data producers (sensors) from data consumers (services as decision-making). Here's how the process typically works:

Data Collection from Sensors: Healthcare sensors continuously collect data such as vital signs, temperature, humidity, or other medical measurements. The residential learning healthcare gateway, acting as a data collection hub, interfaces with these sensors to collect the data. In our demonstration, a Local MQTT broker is installed on the system to allow the communication and data transfer between the sensors and the residential gateway. Where all of the sensors and the gateway act as clients of the local MQTT broker. Data preprocessing steps may be applied to ensure data accuracy and suitability for downstream processing. Preprocessing can include data validation, filtering, normalization, and data enrichment. This step is out of the scope of our demonstration.

MQTT Broker Setup: A local MQTT broker is set up on the residential learning healthcare gateway. MQTT brokers like Mosquitto, HiveMQ, or others are commonly used for this purpose. The broker is configured to handle queues, also known as topics in MQTT, that correspond to different types of sensor data or specific sensors.

Data Publication to MQTT Queues: The healthcare sensors act as MQTT publishers and send the collected data to specific MQTT topics (queues) on the local broker. Each sensor may publish data to its designated queue or topic. In our demonstration, a new queue is created for each sensor topic. ***The Python code box 6.2***: Queue creation provides an example of how queues are created. A queue is created for the trestbps: The person's resting blood pressure senor topic, and another queue is created for the heartbeat sensor topic.

Python codebox 6.2: Queue Creation

```
qTRESTBPS=queue.Queue()

qBeat=queue.Queue()
```

Data Subscription by Data Consumers: Services, as decision-making models, within residential learning healthcare gateway, which need to process or analyze specific types of sensor data, act as MQTT subscribers. These subscribers subscribe to the relevant MQTT topics (queues) based on their data processing requirements.

Queue-Based Data Processing: MQTT's publish-subscribe model ensures that data published to a specific queue (topic) is delivered to all subscribers interested in that queue. Subscribers process the data from their subscribed queues independently and concurrently, allowing for parallel data processing. In our demonstration, the residential learning healthcare gateway includes three types of threads: *subscribe to sensor topics, publish to local decision-making model(s), and publish to the Cloud*. All threads can run at the same time due to queue-based design implemented. ***Python code box 6.3***: *Types of Threads* provide details about the different types of threads created.

Python codebox 6.3: Types of Threads

```
clients=[
# threads publishing to the local decision making
{"broker":"debian","port":8883,"name":"Predict","sub_topic":"none","pub_topic":"TRESTBPSP","qValue":qTRESTBPS,"qPredict":qTRESTBPSPredict},
{"broker":"debian","port":8883,"name":"Predict","sub_topic":"none","pub_topic":"HEARTBEATP","qValue":qBeat,"qPredict":qBeatPredict},
#  threads subscribing to sensor topics
{"broker":"debian","port":8883,"name":"Sensor","sub_topic":"TRESTBPS","pub_topic":"none","qValue":qTRESTBPS,"qPredict":qTRESTBPSPredict},
{"broker":"debian","port":8883,"name":"Sensor","sub_topic":"HEARTBEAT","pub_topic":"none","qValue":qBeat,"qPredict":qBeatPredict},
# threads publishing to the Cloud
{"broker":"broker.hivemq.com","port":1883,"name":"cloud","sub_topic":"none","pub_topic":"TRESTBPS","qValue":qTRESTBPS,"qPredict":None},
{"broker":"broker.hivemq.com","port":1883,"name":"cloud","sub_topic":"none","pub_topic":"HEARTBEAT","qValue":qBeat,"qPredict":None}
]
```

In the python code different types of threads are differentiated by specifying the “name:” attribute and “pub_topic” and “sub _ topic” attributes, and the connection type: Debian or Cloud.

Data Storage (Optional): Processed sensor data may be stored locally in a database or other storage solutions for historical records, analytics, or auditing purposes. This step is out of the scope of our demonstration.

Security and Privacy: Ensuring the security and privacy of healthcare collected data is critical. MQTT supports encryption (e.g., TLS/SSL) for secure data transmission. Access control measures can be implemented on the MQTT broker to control which entities (sensors, services) can publish or subscribe to specific queues. More detailed about TLS/SSL encryption is discussed in the following section.

By implementing queues and MQTT in this manner, residential learning healthcare gateways can efficiently manage and process sensor data while maintaining data integrity and security.

6.2.2.2 Local MQTT Broker Role

To ensure interoperability of the smart gateway with different components of the residential learning healthcare system, there are three levels of interoperability to be fulfilled: Device interoperability (physical connection), Network interoperability (data communication management), and Application-level interoperability [5].

The residential learning healthcare gateway can be built on a single-board computer solution (SBC) as Raspberry Pi, Nvidia Jetson Family, PandaBoard, etc. The choice of the SBC depends on the level of relevance between the SBC specifications and the requirements for the development of the residential learning healthcare solution. The SBC needs to support several communication interfaces such as Wi-Fi, Bluetooth, and Ethernet by built-in components to ensure interoperability between different components of the residential learning healthcare solution. To support communication between sensor nodes based on different communication protocols and the Gateway (SBC), different microcontrollers can be connected to the gateway to enable communication between them. For example, for sensor nodes equipped with nRF, an nRF24L01 chip can be connected to the gateway via SPI. For supporting sensor nodes equipped with 6LoWPAN, a CC2538 module and a SmartRF06 board can be added to the SBC. As for supporting BLE sensor nodes, the smart gateway can be equipped with BLE components as CYBLE-202007. As for Wi-Fi sensor nodes, usually most SBCs have a built-in Wi-Fi chip [2].

To enable device and protocol level interoperability between sensor nodes and the residential learning healthcare gateway, different network topologies, as mesh and star topologies can be implemented. These network topologies use several wireless sensor technologies, such as 6LoWPAN, Wi-Fi and Bluetooth. Mesh-based networks are usually used to tunnel between 6LoWPAN and IPV4/IPV6 protocols, and star-based networks are used to interoperate with non-IP based sensors, i.e., to translate between Bluetooth and IPV4/IPV6 protocols [6].

To provide communication interoperability in modern IoT applications, multiple competing application-level protocols such as CoAP (Constrained Application Protocol), MQTT (Message Queue Telemetry Transport) and XMPP (Extensible Messaging and Presence Protocol) can be used. Each of these protocols has unique characteristics and messaging architecture helpful for different types of IoT applications, which require effective utilization of limited processing power and energy. It's important to note that the choice of communication protocol should be made considering various factors, including the specific requirements of the learning healthcare system, interoperability with existing systems, and compliance with industry regulations [7]. MQTT is a strong candidate for many healthcare scenarios, but its suitability should be assessed in the context of the specific use case and the available infrastructure [8]. In our proposed RLHS architecture, we decided to use MQTT communication protocol to obtain a scalable, interoperable, secure IoT architecture. MQTT is a lightweight, publish-subscribe communication protocol that has several advantages in RLHS compared to other protocols. MQTT is designed to be lightweight, which means it has minimal overhead in terms of message size and processing power required. It uses a publish-subscribe model, which enables efficient one-to-many and many-to-one communication. In RLHS, this can be valuable for broadcasting data from sensors or devices to multiple subscribers (e.g., healthcare providers, caregivers) without requiring individual connections for each subscriber. MQTT is scalable and can handle a large number of devices and clients. In RLHS, this is essential as the number of sensors and devices can grow over time. MQTT brokers can efficiently manage the connections and data flow between different components of learning healthcare systems. MQTT's asynchronous communication model allows devices to send data when it's available without waiting for a response. This is suitable for RLHS, where data from various sensors may not be synchronized and needs to be transmitted as it becomes available. MQTT supports bi-directional communication, making it suitable for not only sending data from sensors to central systems but also for sending commands and notifications back to devices. This is important in healthcare scenarios where remote device control or patient alerts are needed. While MQTT itself doesn't mandate security features, it can be used in combination with security protocols like TLS/SSL for data encryption and authentication. Ensuring the privacy and integrity of healthcare data is paramount, and MQTT can be configured to meet these requirements.

In the proposed system, Mosquitto MQTT broker was installed on a Debian operating system acting as a local broker. To ensure security of the transmitted data between different devices of the residential healthcare system SSL/TLS for transport encryption algorithms are implemented by applying some changes on Mosquitto configuration file installed. Securing communication between MQTT clients and an MQTT broker using SSL/ TLS is essential to protect the confidentiality and integrity of data in transit and the steps to enable SSL/TLS encryption for communication with an MQTT broker are as follows:

Generate or Obtain SSL/TLS Certificates: You'll need SSL/TLS certificates for both the MQTT broker and the clients. You can either generate self-signed certificates for testing or obtain certificates from a trusted Certificate Authority (CA) for production use. The steps we followed in CA creation are explained in ***text box 6.1****: Certificates' creation*.

Text box 6.1: Certificates' creation

Steps to create a CA (to be able to sign on the server and client certificates respectively)
Step 1:
First create a key pair for the CA
Command is: openssl genrsa -des3 -out ca.key 2048
Step 2:
Now Create a certificate for the CA using the CA key that we created in step 1
Command is: openssl req -new -x509 -days 1826 -key ca.key -out ca.crt
Steps to create a server certificate and key
Step 3:
Now we create a server key pair that will be used by the broker
Command is: openssl genrsa -out server.key 2048
Step 4:
Create the server key, please take note of the server domain you need to setup (Later we will be adding multiple domains for authorization)
Command is: openssl req -new -out server.csr -key server.key
Step 5:
Command is: openssl x509 -req -in server.csr -CA ca.crt -CAkey ca.key -CAcreateserial -out server.crt -days 360 -extfile domains.ext
Step 6:
update the mosquitto.conf file to be able to use TLS/SSL and specify the path of the key and certificate, and the port number.
(we will need the conf of the Debian server)
Steps to create a client certificate and key:
Step 7:
Mosquitto.conf updates for the client side
require_certificates – Main setting tells client it needs to supply a certificate when set to true. Default false
use_identity_as_username– – When set to true it tells mosquitto not to use the password file but to take the username from the certificate
(common name given to certificate when you create it). Default false
Step 8:
create a client key
Command is: openssl genrsa -out client.key 2048
Step 9:
create a client certificate
Command is: openssl req -new -out client.csr -key client.key
Step 10:
signing of client key and certificate using our own CA
Command is: openssl x509 -req -in client.csr -CA ca.crt -CAkey ca.key -CAcreateserial -out client.crt -days 360

Configure the MQTT Broker: You'll need to configure the MQTT broker, Mosquitto, to use SSL/TLS by specifying the paths to the certificate files and configuring the TLS settings. The changes we made to the mosquito configuration file are available in the following ***text box 6.2***: *Mosquitto Configuration Changes*.

Text box 6.2: Mosquitto Configuration Changes

```
port 8883
tls_version tlsv1.2
cafile pythonCode/MQTT-Sensor/Mosquitto Config/certs/ca.crt
certfile pythonCode/MQTT-Sensor/Mosquitto Config/certs/server.crt
keyfile pythonCode/MQTT-Sensor/Mosquitto Config/certs/server.key
use_identity_as_username true
require_certificate true
```

listener: Specifies the port on which the broker should listen for secure MQTT connections.

cafile: Points to the CA certificate file if you're using a CA-signed certificate.

certfile: Points to the broker's certificate file.

keyfile: Points to the broker's private key file.

Configure MQTT Clients: MQTT clients (e.g., sensors, gateway, Decision making models, other devices, and applications) need to be configured to use SSL/TLS. You'll need to specify the CA certificate for server verification and, if required, client certificates for mutual authentication. In Python using the Paho MQTT library, you can configure an MQTT client to use SSL/TLS as shown in the ***code box 6.4****: Client Creation with SSL/TLS Encryption.*

Python code box 6.4: Client Creation with SSL/TLS Encryption

```
import paho.mqtt.client as mqtt


client = mqtt.Client()
client.tls_set(ca_certs="/path/to/ca.crt", certfile="/path/to/client.crt",
keyfile="/path/to/client.key")
```

ca_certs: This is the CA certificate file used for server verification.

certfile and **keyfile**: These are client certificate and private key files

6.2.2.3 Local Decision making at the gateway

Local decision-making at a residential learning healthcare gateway refers to the process of analyzing and acting upon data generated within a residential healthcare environment without the need to transmit the data to external servers or cloud-based systems. This approach is often used to ensure real-time, efficient, and privacy-conscious healthcare services within a patient's/consumer's home. Here are some key aspects of local decision-making at a residential learning healthcare gateway:

Data Collection*:* The data collected from different sensors are saved in queues as mentioned earlier in this chapter. But we need to mention here that for each sensor data, two queues are created at the local gateway to solve synchronization issues between the multiple threads in the code. A queue publishes sensor data to the local decision-making model(s). Another queue publishes the same sensor data to the Cloud for advanced analysis. Publishing the same data values to both the local decision-making model and the Cloud ensures better quality of analysis and decision making. Python ***Code box 6.5****: Queues Created to Publish to Decision-making Model (MQTT Client) shows how this is performed in the gateway code.*

Python code box 6.5: Queues Created to Publish to Decision-making Model (MQTT Client)

```
#For each Topic, a new queue is created to publish to the Cloud

qTRESTBPS=queue.Queue()

qBeat=queue.Queue()

#For each Topic Decision-making (prediction), a new queue is created to solve synchronization issues
between the multiple threads.

qTRESTBPSPredict=queue.Queue()

qBeatPredict=queue.Queue()
```

Local Analytics and ML Algorithms*:* The residential learning healthcare gateway typically hosts local analytics and ML algorithms that can process and analyze the collected data. These algorithms can be designed to monitor patient health, detect anomalies, predict potential health issues, or trigger alerts based on predefined patient/consumer requirements. Different local Decision-making models can be added as to the RLHS as independent MQTT clients of the local MQTT broker. ***Figure 6.2*** shows an example of different decision-making models and machine learning algorithms that can be used in such models.

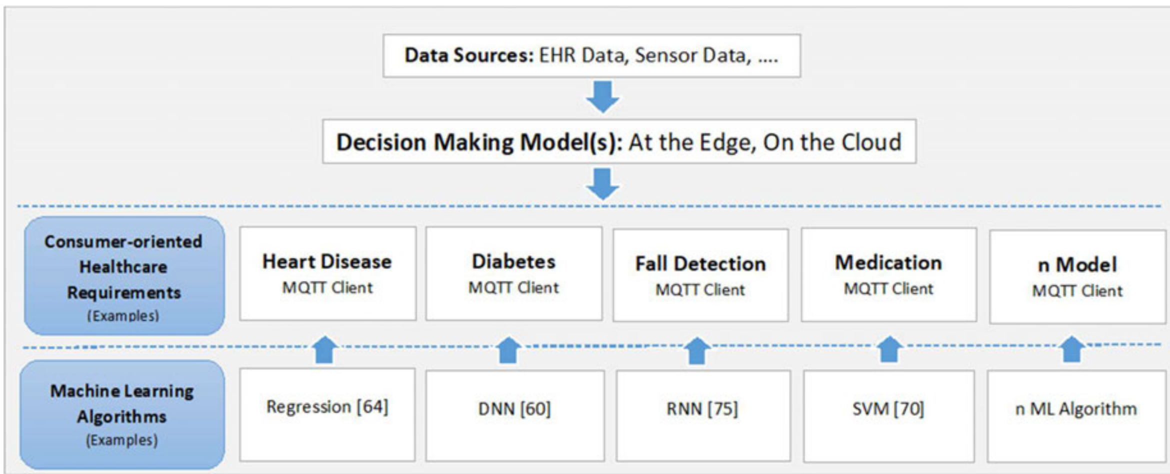

Figure 6.2: Patient/Consumer-oriented Decision-Making Models

Decision Logic*:* Local decision-making involves implementing decision logic within the residential learning healthcare gateway. This logic interprets the analyzed data and determines the appropriate actions or responses. In our demonstration we implemented a decision logic to predict the possibility of a patient encountering a heart disease based on linear logistic regression algorithm. ***Python code box 6.6****: Heart disease Prediction Logic* provides the code we used in our demonstration. Other decision logics can be implemented to perform other tasks.

Python code box 6.6: Heart disease Prediction Logic

```
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.preprocessing import StandardScaler
from sklearn.impute import SimpleImputer
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score
import joblib

class HeartDiseaseClassifier:
  def __init__(self):
    self.model = None
    self.heart_df = None

  def train(self, data_file):
        # Load the dataset
    self.heart_df = pd.read_csv(data_file)

    # Preprocess the data
    #self.heart_df = self.preprocess_data(self.heart_df)

    # Split the data into features and target
    X = self.heart_df.drop('target', axis=1)
    y = self.heart_df['target']

    # Split the data into training and testing sets
    X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)

    # Create and train the logistic regression model
    self.model = LogisticRegression()
    self.model.fit(X_train, y_train)

    # Evaluate the model on the test set
    y_pred = self.model.predict(X_test)
    accuracy = accuracy_score(y_test, y_pred)
    print(f"Accuracy: {accuracy}")
    joblib.dump(self.model, 'heart_disease_model.joblib')

  def load_model(self, model_file):
    # Load a trained model from disk
    self.model = joblib.load(model_file)
    self.heart_df = pd.read_csv('heart.csv')

  def predict(self, csv_file):
    test_data = pd.read_csv(csv_file)
```

```
    # Preprocess the test case data
    #test_data = self.preprocess_data(test_data)
    if 'target' in test_data.columns:
      test_data = test_data.drop('target', axis=1)

    # Make predictions
    predictions = self.model.predict(test_data)

    return predictions

  def create_test_case_csv(self, age, sex, cp, trestbps, chol, fbs, restecg, thalach, exang, oldpeak, slope,
ca, thal, csv_file):
      # Get the column names from the original DataFrame
    original_columns = self.heart_df.columns.tolist()

  # Create the test case dictionary with default values
    test_case_dict = {column: [0] for column in original_columns}

  # Update the test case dictionary with the provided feature values
    test_case_dict['age'] = [age]
    test_case_dict['sex'] = [sex]
    test_case_dict[f'cp'] = [1]
    test_case_dict['trestbps'] = [trestbps]
    test_case_dict['chol'] = [chol]
    test_case_dict['fbs'] = [fbs]
    test_case_dict[f'restecg'] = [1]
    test_case_dict['thalach'] = [thalach]
    test_case_dict['exang'] = [exang]
    test_case_dict['oldpeak'] = [oldpeak]
    test_case_dict[f'slope'] = [1]
    test_case_dict['ca'] = [ca]
    test_case_dict[f'thal'] = [1]

  # Create a DataFrame from the test case dictionary
    test_case_df = pd.DataFrame.from_dict(test_case_dict)

  # Save the DataFrame to a CSV file
    test_case_df.to_csv(csv_file, index=False)
    return test_case_df
```

And later, used this decision logic in the Heart disease Prediction Client to calculate the patient's/consumer's probability of encountering a heart disease based on sensor data collected and heart disease CSV file used for decision model training and testing. The queues and the MQTT client created for heart disease prediction in the residential learning healthcare gateway are displayed in the *python **code box 6.7**: Decision-making topics and Clients Creation sample*.

Python codebox 6.7: Decision-making topics and Clients Creation sample

```
#For each decision making Topic, a new queue is created to publish to the Cloud

qPREDICTIONVAL=queue.Queue()

#For each Topic Decision-making (prediction), a new queue is created to publish results/feedback to the local gateway .

qPREDICTION=queue.Queue()

# creating a client for the heart disease prediction model

{"broker":"debian","port":8883,"name":"Sensor","sub_topic":"FinalPredict","pub_topic":"none","qValue":qPREDICTIONVAL,"qPredict":qPREDICTION},
```

In this manner, the residential learning healthcare gateway can take real-time actions based on its decision logic. These responses may include sending notifications or alerts to healthcare providers, caregivers, or family members, adjusting medical device settings (e.g., insulin dosage) based on patient condition, or providing feedback or guidance to the patient via a user interface.

Integration with Remote Systems (Optional): In some cases, the residential learning healthcare gateway may integrate with remote healthcare systems through the Cloud, such as Electronic Health Records (EHRs) or telemedicine platforms, to share relevant data when necessary for remote monitoring or consultations. This aspect is outside the scope of the demonstration.

User Interface: The gateway often features a user-friendly interface for patients and caregivers to access data, receive alerts, and interact with the system which is also outside the scope of our demonstration.

Local decision-making at a residential healthcare gateway offers several advantages, including reduced latency, improved data privacy, and the ability to continue functioning even in the absence of a stable internet connection. It plays a crucial role in supporting the growing trend of remote patient monitoring and home-based healthcare services.

6.2.3 Cloud Services

Cloud services play a crucial role in residential learning healthcare systems by providing a scalable, secure, and centralized platform for collecting, storing, processing, and analyzing health-related data in case of internet availability. This enables real-time monitoring, data-driven insights, and timely interventions to improve the well-being of patients/consumers in their homes. Although Local decision-making at the residential learning healthcare gateway solves the problem of decision-making in absence of internet availability, the decision-making and data analysis that can be provided at the Cloud is more advanced. Cloud services can leverage machine learning models and predictive analytics to identify patterns and potential health issues based on historical data. This can help in early intervention and personalized care. Cloud services offer scalability to handle increasing data volumes and device connections as more individuals use the monitoring system. Redundancy ensures system reliability and fault tolerance.

In our demonstration, the Cloud layer consists of a global data handling hub performing heavy computational tasks on the collected and stored data, a cloud based MQTT broker that allows communication with the local MQTT broker at consumer's residence, and a decision-making model(s) supporting advanced machine learning algorithms for more powerful data analysis and decision making.

To demonstrate how the proposed residential learning healthcare gateway is connected and communicates with the Cloud, in the gateway code, we created a thread to publish sensor data to the cloud MQTT Broker. The same data is published by another thread to the local MQTT Broker to avoid any contradictions in the analysis processes between the local decision-making models and the cloud decision-making models. The data is published to the MQTT broker on the Cloud to specific topics on the CLOUD MQTT Broker, and received by Cloud services which are clients of the Cloud MQTT broker subscribing to the specific topics. Data analysis and decision making at the Cloud is out of the scope of our demonstration. *Python* ***code box 6.8****: Clients and* *corresponding Topics on the Cloud* shows the code for creating Cloud Clients that receive published data from specific sensors. Finally, it is important to mention that with Cloud MQTT we don't need to worry about data security and privacy since it's a built-in feature in Cloud MQTT brokers as HiveMQ.

Python code box 6.8: Clients and corresponding Topics on the Cloud

```
clients=[
{"broker":"broker.hivemq.com","port":1883,"name":"cloud","sub_topic":"none","pub_topic":"TRESTBPS","qValue":qTRESTBPS,"qPredict":None},
{"broker":"broker.hivemq.com","port":1883,"name":"cloud","sub_topic":"none","pub_topic":"HEARTBEAT","qValue":qBeat,"qPredict":None}
]
```

References

[1] Institute of Medicine (US) Roundtable on Evidence-Based Medicine, the Learning Healthcare System: Workshop Summary, National Academies Press (US), Washington (DC), 2007.

[2] Gia, T. N., Dhaou, I. B., Ali, M., Rahmani, A. M., Westerlund, T., Liljeberg, P., & Tenhunen, H. (2019). Energy efficient fog-assisted IoT system for monitoring diabetic patients with cardiovascular disease. *Future Generation Computer Systems*, *93*, 198-211.

[3] A. Elsts *et al.*, "Enabling Healthcare in Smart Homes: The SPHERE IoT Network Infrastructure," in *IEEE Communications Magazine*, vol. 56, no. 12, pp. 164-170, December 2018, doi: 10.1109/MCOM.2017.1700791.

[4] Elsts, Atis & Burghardt, Tilo & Byrne, Dallan & Damen, Dima & Fafoutis, Xenofon & Hannuna, Sion & Ponce-López, Víctor & Masullo, Alessandro & Mirmehdi, Majid & Oikonomou, George & Piechocki, Robert & Tonkin, Emma & Vafeas, Antonis & Woznowski, Przemyslaw & Craddock, I.J. & Holmes, Michael. (2018). A Guide to the SPHERE 100 Homes Study Dataset.

[5] Terence K.L. Hui, R. Simon Sherratt, Daniel Díaz Sánchez, Major requirements for building Smart Homes in Smart Cities based on Internet of Things technologies, Future Generation Computer Systems, Volume 76, 2017, Pages 358-369, ISSN 0167-739X, https://doi.org/10.1016/j.future.2016.10.026.

[6] A. -M. Rahmani *et al*., "Smart e-Health Gateway: Bringing intelligence to Internet-of-Things based ubiquitous healthcare systems," *2015 12th Annual IEEE Consumer Communications and Networking Conference (CCNC)*, Las Vegas, NV, USA, 2015, pp. 826-834, doi: 10.1109/CCNC.2015.7158084.

[7] M. Amoretti, R. Pecori, Y. Protskaya, L. Veltri and F. Zanichelli, "A Scalable and Secure Publish/Subscribe-Based Framework for Industrial IoT," in *IEEE Transactions on Industrial Informatics*, vol. 17, no. 6, pp. 3815-3825, June 2021, doi: 10.1109/TII.2020.3017227.

[8] P. Desai, A. Sheth and P. Anantharam, "Semantic Gateway as a Service Architecture for IoT Interoperability," *2015 IEEE International Conference on Mobile Services*, New York, NY, USA, 2015, pp. 313-319, doi: 10.1109/MobServ.2015.51.

Chapter 7: Discussion

The set of requirements proposed in Chapter 5, and the residential LHS architecture presented in chapter 6 inspires consumer healthcare researchers to divert from developing fixed gateways that are non-adaptive, and limited to one or two medical conditions, toward implementing the requirements of adaptive gateway that we are proposing in this research, i.e., an adaptive gateway in residential learning healthcare systems. The idea behind the proposed requirements is to achieve a holistic residential learning healthcare system with an adaptive gateway that has a set of characteristics. A gateway that adapts with different consumer needs that varies between monitoring, detection, and prediction of health conditions. A gateway that adapts with changing medical conditions for a consumer over time. A gateway that ensures the security and privacy of the consumer and can adapt to new technologies in the domain. A gateway that guarantees Internet connectivity and interoperability using various adaptable communication technologies. A gateway that is scalable in the means of introducing new components to the hardware (e.g., sensors, memory cards) and/or software. All these characteristics combined promote the development of a one and for all gateway system. A cheaper gateway that is suitable for any consumer's needs and that can continuously adapt with each consumer's needs over time.

This chapter discusses how the proposed requirements for an adaptive gateway in residential LHS facilitates the implementation of the proposed adaptive gateway.

Although addressing all the presented requirements was not applicable in our research due to resource, personnel, and time limitations. Still, to evaluate the importance of the proposed requirements we selected a set of requirements and implemented them in a proof-of-concept demonstration. The requirements addressed in the demonstration are:

- ✓ Ensuring Interoperability and network availability at the edge
- ✓ Developing a scalable system
- ✓ Designing a consumer-oriented system
- ✓ Implementing a service-oriented architecture
- ✓ Implementing Local decision making

Edge-based computing in healthcare functions by extending the cloud computing paradigm to the edge of the network enabling new services such as local data processing, storage, and decision making in residential LHSs [1]. Based on the results of the demonstration performed in this research, we have conceptually proven the design of the RLHS architecture and on a theoretical level this should improve the quality of healthcare monitoring and QoL of patients. However, the implementation of the system is a further requirement to be fulfilled as final evidence of our system's superiority in these respects. We were able to show how Edge computing can significantly improve the quality of healthcare home monitoring. As it allows data processing to occur closer to the source, which means that healthcare data from monitoring devices can be processed and analyzed in real-time or near real-time. This reduced latency ensures that critical health information is acted upon quickly, potentially saving lives in emergency situations. We also showed how Edge computing can enhance privacy and security of patient's/consumer's healthcare data through keeping the data localized, reducing the need to transmit it over long distances and decreasing the risk of data breaches during transmission [2].

Edge computing enables monitoring devices to function offline or with intermittent connectivity. Data can be stored locally and transmitted when a stable connection is available. Edge computing can be easily scaled to accommodate a growing number of monitoring devices and patients. New edge devices can be added to the network as needed without overloading centralized cloud servers. Healthcare providers can customize edge computing solutions to meet their specific monitoring and analysis needs. This flexibility allows for tailored solutions that align with the unique requirements of different patients/consumers.

The Edge computing paradigm depends on how IoT devices can be programmed to interact with each other and run user defined codes [3]. Thus, in our proof-of-concept we concentrate on programming the gateway and sensors to enable communication and data transmission at the Edge. The implementation of a local MQTT broker [4] is a one and for all solution that enables communication between devices independently of internet availability, provides security and privacy of the transmitted data using SSL/TLS certificates, enables scalability of the residential LHS since with MQTT each device or service is considered as an independent client and MQTT enables the creation of unlimited number of clients.

The implementation of a local MQTT broker at the Edge permits various devices and services in the residential LHS to perform independently as clients, where different operations are properly defined and altered without degrading the interoperability of the system [5]. Thus, enabling the system to have a Service Oriented Architecture (SOA).

The Local MQTT broker with the client feature allows the development of a consumer oriented LHS [6]. MQTT allows for a publish-subscribe model, where clients (devices, applications, decision making models) can subscribe to specific topics of interest. Thus, patients/consumers can have their own dedicated MQTT topics, enabling them to access and monitor their own health data based on their healthcare requirements. This patient-centric approach enhances consumer engagement in their healthcare and enables a better QoS.

Edge computing and the implementation of a local MQTT broker played a major role in enabling real-time decision making at the edge. Where, with the help of the client feature in MQTT and the availability of the data close to the source due to edge computing, we were able to implement decision making models using machine learning algorithms for different healthcare scenarios that can work independently using data from various data sources (clients) through subscribing to different topic of interest.

Thus, the demonstration performed verified that edge computing and MQTT communication protocol improves the quality of residential LHS by making it more responsive independent of internet availability, secure, efficient, and adaptable to various healthcare scenarios. It enhances patient outcomes by ensuring timely interventions and reducing the burden on healthcare infrastructure.

References

[1] M. Hartmann, U. S. Hashmi, and A. Imran, "Edge computing in smart health care systems: Review, challenges, and research directions," Transactions on Emerging Telecommunications Technology, vol. 33, no. 3, pp. e3710, Aug. 2019. doi: 10.1002/ett.3710.

[2] W. Yu, F. Liang, X. He, W. G. Hatcher, C. Lu, J. Lin, and X. Yang, "A survey on the edge computing for the internet of things," IEEE Access, vol. 6, pp. 6900-6919, Nov. 2017. doi: 10.1109/ACCESS.2017.2778504.

[3] Y. Nan, W. Li, W. Bao, F. C. Delicato, P. F. Pires, and A. Y. Zomaya, "Cost-effective processing for delay-sensitive applications in cloud of things systems," in Network Computing and Applications (NCA), 2016 IEEE 15th International Symposium on, pp. 162-169, IEEE, 2016.

[4] P. Desai, A. Sheth, and P. Anantharam, "Semantic Gateway as a Service Architecture for IoT Interoperability," in 2015 IEEE International Conference on Mobile Services, pp. 313-319, 2015. doi: 10.1109/MobServ.2015.51.

[5] K. Avila, P. Sanmartin, D. Jabba, and M. Jimeno, "Applications based on service-oriented architecture (SOA) in the field of home healthcare," Sensors, vol. 17, no. 8, p. 1703, Jul. 2017. doi: 10.3390/s17081703.

[6] S.-Y. Lee, P.-W. Huang, M.-C. Liang, J.-H. Hong, and J.-Y. Chen, "Development of an arrhythmia monitoring system and human study," IEEE Trans. Consum. Electron., vol. 64, no. 4, pp. 442–451, Nov. 2018. doi: 10.1109/TCE.2018.2875799.

Chapter 8: Conclusions

The process of research and design of smart adaptive residential learning healthcare systems is very important and requires deep understanding, exploration, and implementation to effectively deploy such systems. Healthcare conditions are challenging, and change over time, requiring monitoring over extended periods during which many decisions may be undertaken. Current residential healthcare systems do not easily enable consumers in the home to receive, integrate, or analyze healthcare data from different data sources.

Thus, this research has presented, for the first time, the requirements for creating residential learning healthcare systems (LHS) gateways for consumers that are fundamentally adaptive and support decision making, enabling a range of future consumer products and services to offer holistic management of their changing health conditions overtime. A system that performs continuous monitoring, self-configuration, exploration of new healthcare conditions, ensuring data privacy and security, and enables decision making locally.

In this research we discussed the implementation of a set of requirements from the proposed list of requirements. We developed a demo of an edge-based gateway merging cloud and edge computing as discussed in chapter 6. We presented and explained how the proposed gateway is consumer-oriented and scalable. And finally, demonstrated network availability at the edge to enable local decision making.

The limitations of this research work lie in its disability to implement all the requirements proposed for the development of a residential learning healthcare system. It excluded important requirements such as merging EHR data sources with the developed residential LHS and integrating it with a real-world cloud service for advanced analysis and decision making due to resources, personnel, and time constraints. Although these two requirements are essential to attain the holistic perspective of the proposed residential LHS architecture.

The procedure of merging EHR data sources with sensor data for relevant and valuable data generation and analysis is of great interest for researches. Recently, various ML models have been proposed to extract features from textual EHR and fuse it with sensor data in healthcare monitoring systems. Thus, information extraction and fusion models and feature identification models using various ML algorithms are crucial to improve the proposed residential LHS accuracy and decrease the error rate.

The adoption of Cloud technologies in the context of healthcare has been termed Healthcare as a Service (HaaS). HaaS applications benefit healthcare monitoring systems through being scalable, on-demand, and provide virtually infinite computation, storage, networking resources, and advanced analytical services. Thus, integrating HaaS applications to the proposed residential LHS would ultimately enhance the accuracy in decision making and quality of service delivered to the consumer/patient.

Therefore, the future directions of this work would be the implementation of the uncovered requirements in our proof-of-concept. Requirements as the integration of the proposed RLHS with remote data sources like EHR data, and system integration with remote cloud services for advanced analysis and decision making as discussed in previous paragraphs of this chapter.

Another future goal would be the implementation of a local data storage solution to store processed sensor data for historical records, analytics, or auditing purposes. Data storage is a major concern in healthcare systems, as personal and confidential information is used in such systems. Thus, more attention needs to be given to local storage and information processing management in edge-based residential healthcare solutions. One solution would be the development of a hybrid storage architecture by building a global blockchain in the cloud service layer and local blockchain at the edge.

All the mentioned future directions are ultimate future goals that serve more accurate consumer-oriented decision making in residential LHSs that requires researchers' attention. And the ability to implement the overall Residential LHS in a real word scenario and test it with varying consumers' requirements would be the substantial achievement of this research work.