Requirements for adaptive consumer gateways in residential learning healthcare systems: bringing intelligence to the edge

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Title:
Requirements for Adaptive Consumer Gateways in Residential Learning Healthcare Systems: Bringing Intelligence to the Edge

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Abstract:

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. This leads to the exciting potential of a new research field in consumer-oriented gateways and consumer products that can adapt to the consumer's healthcare needs, learn about the consumer, and over time can adapt accordingly. While consumer healthcare gateways exist, they have tended to be fixed on specific medical conditions and are not upgradeable or adaptive. To be able to create adaptive consumer gateways for consumer healthcare applications, this paper identifies a set of requirements concerning scalability, energy efficiency, reliability, availability, interoperability, and privacy that need 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 serve the development process are also discussed. The goal of this paper is 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.

Index Terms:

Adaptive gateways, Residential Healthcare systems, Learning Healthcare Systems, Edge Computing, Machine Learning

I. INTRODUCTION

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) and 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 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 non-resource constrained 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 paper. However, this paper now calls for a paradigm shift from the current fixed 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 consumers could purchase home healthcare LHS gateways, but as the 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 paper.

The specific research contributions from this position paper are as follows:

1. This is the first call for consumer gateways to become adaptive, follow the LHS paradigm, and enable the consumer field to become aware of the advantages of LHS for the consumer.
2. We present for the first time the technical requirements and challenges that need to be satisfied, solved, and implemented, to create consumer based adaptive healthcare gateways.
3. This position paper is also the first to provide a holistic identification of the technical requirements for the development of adaptive consumer gateways in residential learning healthcare systems.
4. To demonstrate the concept, we present a proof-of-concept residential LHS with a consumer oriented adaptive gateway architecture based on machine learning applied on consumer's cardio data.

Currently, there are no published requirements, or recommendations on how to create LHS systems. Thus, from our research, we present technical requirements that define and then guide researchers to develop adaptive consumer gateways in the future that can adapt to the changing needs of the consumer overcoming all the limitations of previously developed fixed consumer gateways. The proposed requirements in this paper enable the shift from residential healthcare systems that are non-adaptive over time, fixed to one or two medical conditions, and that are mainly dependent on the cloud in data analysis and decision making to adaptive consumer-oriented learning healthcare systems, which we believe are the future of mass market residential consumer healthcare systems. The holism of the requirements lies in covering the advancements needed in all components of learning healthcare systems, data sources quality and feature extraction methods, gateway architecture and capabilities, and decision support system location and effectiveness.

The rest of the paper is as follows. Chapter II presents a review of the state of the art of LHSs, gateway architectures and functionalities concluding the need for adaptive gateways. Then data sources that offer the most benefit for the efficiency and reliability of adaptive gateways in healthcare are identified. Furthermore, different machine learning methods for data analysis and real-time decision making that are suitable for the consumer implementation of adaptive gateways in healthcare LHSs are discussed. Chapter III presents the requirements for consumer-based home LHS systems. Chapter IV presents our proof-of-concept demonstration. In Chapter V we discuss the research implications. Finally, Chapter VI presents our conclusions and potential future research directions.

II. Learning Healthcare Systems

It is the nature of this topic that many terms exist, therefore Table I presents the nomenclature for this paper.

TABLE I
NOMENCLATURE

Term	Description
6LoWPAN	IPv6 over Low-Power Wireless Personal Area Networks
ASCO	American Society of Clinical Oncology
BLE	Bluetooth Low Energy
BN	Bayesian Networks
CDS	Clinical Decision Support
CDSS	Clinical Decision Support System
CER	Comparative Effectiveness Research
CI	Cohort Identification
CNN	Convolutional Neural Network
DL	Deep Learning
DNN	Deep Neural Networks
DSS	Decision Support System
EBM	Evidence-Based Medicine
ECG	Electrocardiogram
EHR	Electronic Health Record
HDG	Healthcare Data Gateway
IA	Intelligent Assistance
ICT	Information and Communication Technology
IoT	Internet of Things
LHS	Learning Healthcare Systems
ML	Machine Learning
MQTT	Message Queuing Telemetry Transport
ND	Negative Deviance
NLP	Neuro Linguistic Programming
NN	Neural Networks
PCROM	Predictive Care Risk and Outcome Model
PD	Positive Deviance
PM	Precision Medicine
PPRM	Predictive Patient Risk Modelling
QoE	Quality of Experience
QoS	Quality of Service
RNN	Recurrent Neural Network
S	Surveillance
SARSA	State-Action-Reward-State-Action
SBC	Single Board Computer
SOA	Service Oriented Architecture
SPI	Serial Peripheral Interface
SSL/TLS	Secure Sockets Layer and Transport Layer Security
SVM	Support Vector Machines
WBAN	Wireless Body Area Network
Zigbee	Zonal Intercommunication Global standard

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].

A. 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 relations 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).

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 nine LHS classification types shown in Fig. 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 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].

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

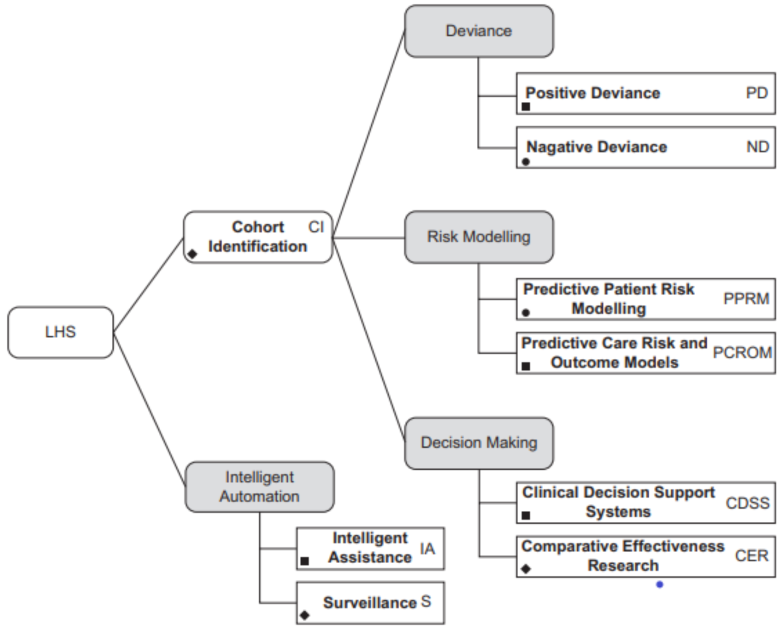

Fig. 1. Learning Healthcare Systems Taxonomy [12].

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. And since EHR is a major data source for LHS, this indicates LHS is inheriting problems from the EHR. 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].

B. Data Sources

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 Recurrent 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 diversity 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].

C. Gateways

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].

D. Machine Learning

Machine learning plays a fundamental role in the development in LHS systems [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.

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 based on an identified collection of predictors. Classification is one of the most widely used methods of data mining in healthcare organizations [65]. Classification 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. SVM is one of the most popular approaches that are used by researchers in healthcare field for classification [67, 68, 69]. Seint *et al.* [70] proposed the use of a SVM model for automatic understanding of medication and meal intake monitoring.

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, 72, 73].

Neural networks and deep learning algorithms are another subset of ML that 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] are introduced in various healthcare monitoring systems.

Ensemble learning methods another subset of ML showed improved classification performance in the biomedical and healthcare fields [76, 77, 78].

Reinforcement learning comprises of a set of algorithms such as Q Learning and State-Action-Reward-State-Action (SARSA). Such algorithms are used in home healthcare monitoring systems to prioritize urgent messages to ensure emergency situations are handled on time [79, 80].

To identify which ML algorithms to be implemented in an LHS, the designer needs to identify whether the purpose 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.

III. Proposed Requirements for an Adaptive Gateway in Consumer Residential Learning Healthcare Systems

In this section we propose a set of requirements for the development of adaptive gateways for residential LHSs that enhance the consumer healthcare experience. The gateway is to be located at the edge, at the 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. 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. The data phase handles the attainment and mining of prior data collected from a variety of data sources such as EHR 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 [12] that focuses on individual patients and brings systematized PM solutions. Thus, a 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 to ensure the quality and accuracy of the data to be used later for decision making. 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 [83]. Unfortunately, there is no single-best algorithm for every dataset, including biomedical datasets [84]. 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 [84]. But it is best to be used with numerical data since clustering algorithms have problems in the conversion from categorical to numerical data [84].

The knowledge phase is responsible for applying sophisticated and analytical methods on the aggregated, classified, or categorized data to harness the knowledge concluded using ML methods for the detection, prediction, and monitoring of chronic diseases, aspects of health deterioration, and dangerous physical situations [81, 82]. The evaluation phase uses suitable ML algorithms that showed promising results in analyzing different features in mined data such as SVM, Neural Networks (NN), and Deep Learning (DL) for decision making based on the outcomes of the knowledge phase SVM and neural networks in combination with ensemble algorithms showed superior results in decision making scenarios [34]. 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 [84].

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 throughout the ability to modify the choice of collected data and the analysis process of collected data 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 consumer.
- The cost efficiency of the proposed system lays in its unified nature that allows its adaptation based on the needs of each consumer.
- Availability is achieved by setting the gateway at the premises of the consumer making the analysis and the decision-making process local.

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 [37, 85].
- For network availability different communication technologies may be used for short range communication such as RFID, Wi-Fi, Zigbee, Bluetooth [86]. 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 [87]. 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 EHRss that are stored in the blockchain [87]. 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 [88].
- 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 [87].
- Real-time monitoring in LHSs can be possible throughout the integration of nanoelectronics, big data, and IoT [89].
- For local-edge analytics and decision making to be achieved there is a need to shift reasoning towards the edge using software as TinyML and hardware 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 [90, 91].

From the results of our research, Table II 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 II
LIST OF REQUIREMENTS FOR RESIDENTIAL LHS

Requirement	References	Description
A. Requirements for LHS architecture		
Apply sequential phases	Lambin et al. [14].	Data collection phase, knowledge phase, application phase, and evaluation phase.
Adopt Heimdall taxonomy and framework	McLachlan et al. [10], McLachlan et al. [12].	To improve the focus on the individual consumer's health.
B. Requirements for Data Sources		
Develop an optimal EHR user interface	Brown et al. [28], CM&MS [29].	Improve consistency of data entry and decrease unstructured, uninterpretable data in the EHR.
Use ML algorithms to Structure and remodel the available EHR data	Jiang et al. [30].	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. [34].	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. [44], Sarabia-Jácome et al. [51], Miettinen et al. [52], Yu et al. [53] Hu et al. [54], Cao et al. [55].	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. [16].	To overcome the architectural limitations of both computing systems.
Scalable	Alrawais et al. [59], Rachakonda et al. [60], Mouradian et al. [62].	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. [57].	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. [44], Alrawais et al. [59], Zebari et al. [71].	Has a unified nature that allows its adaptation based on the needs of each consumer.
Uses Service Oriented Architecture (SOA)	Kim et al. [37], Avila et al. [85].	Permits various devices in the system to perform independently.
Ensures edge network availability	Ghamari et al. [86].	Use short range communication technologies as RFID, Wi-Fi, Zigbee, and Bluetooth at the edge.
Ensures security and privacy	Pradhan et al. [87], Yue et al. [88].	Deploy blockchain technologies.
Power efficient.	Pradhan et al. [87].	Generate power using renewable energy systems.

IV. Proposed Residential LHS with consumer-Oriented Adaptive Gateway Architecture and Implementation

In this section, we present the architecture of the proposed proof-of-concept residential LHS demonstrator as presented in this work and implemented a set of the proposed requirements for the adaptive consumer-oriented gateway. The architecture of the proposed system shown in Fig. 2 consists of three main layers: Sensor nodes layer, Edge computing layer including a Consumer-oriented adaptive gateway, and a cloud computing platform (Back-end).

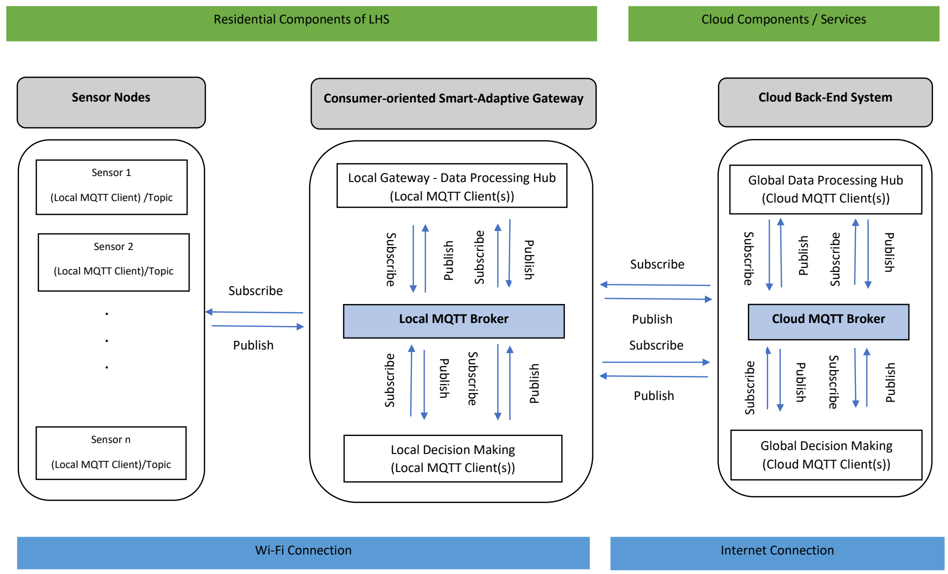

Fig. 2. Proposed Residential LHS Architecture.

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 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. 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 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 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 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 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 Fig. 3. These decision-making models are specified and implemented based on the consumer's diverse and changing healthcare needs. 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 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.

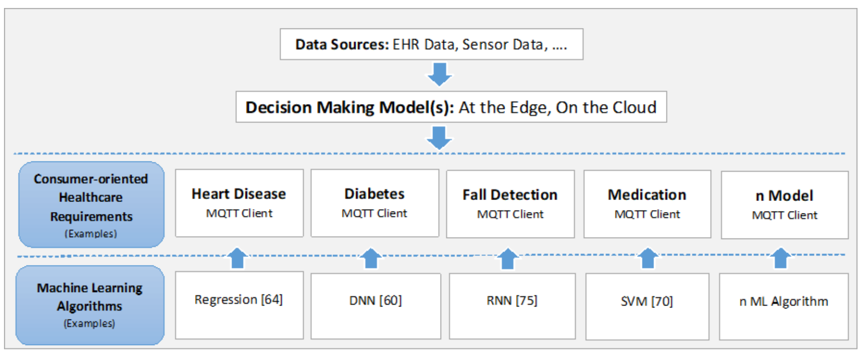

Fig. 3. Consumer-oriented Decision-Making Models.

Table III is a summary table to present the categories of data sources, gateways, and machine learning algorithms.

TABLE III
SUMMARY PRESENTATION

<table>
<tr><th colspan="2">Data Sources</th><th>Machine Learning Algorithms</th></tr>
<tr><td colspan="2">EHR data [26] [27]</td><td rowspan="3">Neural network and deep learning algorithms (RNN, Autoencoder…) for feature extraction [30], speech recognition, visual disease recognition, and disease detection [60] [64] [74] [75].</td></tr>
<tr><td colspan="2">Patient/ Disease Registries [31] [32]</td></tr>
<tr><td colspan="2">Complementary data: sensors, cameras, etc. [35] [48]</td></tr>
<tr><td colspan="2">Gateways</td><td rowspan="3">Clustering algorithms (k-means, dimensionality reduction...) for data compression [34] [71] [72] [73].</td></tr>
<tr><td rowspan="3">Fixed Gateways [35] [36] [37] [38] [39] [40] [41]</td><td>Smart Gateways</td></tr>
<tr><td>Cloud-based Gateways [42] [43] [45] [46] [47] [48] [49] [50]</td></tr>
<tr><td>Edge-based Gateways [51] [52] [53] [54] [55] [56] [57] [58] [59] [60] [61]</td><td rowspan="3">Classification algorithms (SVM, k-nearest neighbors…) for data mining [65] and various healthcare monitoring systems [67] [68] [69] [70].</td></tr>
<tr><td colspan="2">Decision Making</td></tr>
<tr><td colspan="2">Heart diseases [42] [57] [67] [68] [69] [89]</td></tr>
<tr><td colspan="2">Fall detection [48] [75]</td><td rowspan="3">Regression algorithms (Linear regression, LARS…) to predict the onset of chronic diseases [64].</td></tr>
<tr><td colspan="2">Chronic disease Prediction [66] [81]</td></tr>
<tr><td colspan="2">Nutrition [60] [70]</td></tr>
<tr><td colspan="2">Dementia [43]</td><td rowspan="3">Reinforcement learning (Q learning, SARSA…) for handling emergency situations [79] [80].</td></tr>
<tr><td colspan="2">Diabetes [64]</td></tr>
<tr><td colspan="2">Medication [70]</td></tr>
</table>

V. DISCUSSION

The set of requirements proposed in section III, and the residential LHS architecture presented in section IV 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 position paper, 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.

VI. CONCLUSION AND FUTURE DIRECTIONS

The process of building 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 paper 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 paper 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. 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 future directions of this work would be the implementation of the uncovered requirements in our proof-of-concept. Requirements as implementing a local data storage solution to store processed sensor data for historical records, analytics, or auditing purposes. Another future goal would be the integration of the proposed RLHS with remote data sources like EHR data. Creation of a user interface for consumers and caregivers to access data, receive alerts, and interact with the system is also a requirement to be fulfilled in the future. System integration with remote cloud services for advanced analysis and decision making is an ultimate future goal that serves more accurate consumer-oriented decision making through merging both edge and cloud computing. And as a later step, we plan to implement the overall Residential LHS in a real word scenario and test it.

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