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RESEARCH ARTICLE

An Evaluation of Unobtrusive Sensing in a Healthcare Case Study

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ABSTRACT This paper examines the integration of Human-in-the-Loop Cyber-Physical Systems (HiTL-CPS) and Unobtrusive Sensing through a case study named *iFriend*. Our approach enhances the data acquisition phase of HiTLCPS by integrating unobtrusive sensing techniques to monitor real-time heart rate and breathing rate. This is achieved by leveraging Channel State Information (CSI) of Wi-Fi signals, specifically focusing on its amplitude information. This integration facilitates seamless interaction between humans and the cyber-physical environment. We detail the architecture of the *iFriend* system, comprising sensors, actuators, and computational units forming a closed-loop control mechanism. The unobtrusive sensing module is specifically designed to capture physiological changes without causing discomfort or interfering with daily activities, making it well-suited for healthcare applications and human-machine interaction. We assess *iFriend* in an experimental setting, demonstrating its feasibility, with between 80% and 90% of estimates hovering around 2.5 breaths per minute for BR or 10 beats per minute for HR, respectively.

INDEX TERMS CSI, human-in-the-loop, IoT, unobtrusive sensing.

I. INTRODUCTION

Now, more than ever, we have extremely large amounts of data at our disposal. For instance, a supermarket chain can deal with hundreds of thousands of products equipped with Radio Frequency IDentifiers (RFID), and use RFID readers to scan these items every second, generating about 12.6 GBytes of data per second and about 544 TBytes of data per day [1]. Building on the available data, the number of smart systems is also increasing. The European Technology Platform on Smart Systems Integration (EPoSS) defines smart systems as systems that *"are able to sense, diagnose, describe, qualify and manage a given situation,…They are able to interface, interact and communicate with users, their environment and with other Smart Systems"* [2].

Smart systems should be able to perform and incorporate functions of sensing, actuation, and control, in order to describe and analyse a specific situation and make decisions based on the available data. In most cases, the smartness of the system can be attributed to autonomous operation based on closed loop control, energy efficiency, and networking capabilities. However, despite the fact that current systems are "smart" in many ways, the majority of them ignore the human factor, or treat humans as a mere source of data [3]. To achieve a truly smart system, we need to work on the integration of humans as part of the closed-loop process proposed by a cyber-physical system. That is, humans need to be considered in every phase of the loop.

At the same time, we are witnessing the emergence of new sensor techniques [4], [5], that show the importance of humans within the sensing system. In our opinion, only a system that is able to extend its capabilities to perceive

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and adapt to human actions, intentions, and emotional states, can be considered a truly smart system. And only then we can enter the realm of HiTLCPS, where humans and machines interact, cooperate, coexist, and enhance our current environment.

To achieve this goal, we first need to endow our systems with sensory capabilities that are tailored to perceive humans. One way to do this is by using personal devices. Smartphones have become a constant in human lives, as most of us carry at least one at all times during the day, and we even sleep with these devices next to us. Smartphones have evolved tremendously in the last few years. They now have high processing power, their batteries last for several days, their networking capabilities allow for fast and reliable communications, and they are packed with many sensors (e.g., accelerometer, gyroscopes, barometers, GPS).

Furthermore, they even incorporate virtual sensors (i.e., software entities that virtualize sensor capabilities), like, for instance, step counter sensors which work by inferring of the accelerometer values. We are also able to run complex models on these devices to capture context information, such as changing from one vehicle to another or reaching a certain location. These devices also offer Application Programming Interfaces (APIs) that allow us to create custom code to run on them. Additionally, these APIs allow us to even retrieve data that can be directly correlated with human health or physical states, such as activity levels and sleep patterns. As such, we can now leverage these devices to create systems that better account for humans, that is, to create HiTLCPS.

Although smartphones are an *entrypoint* into human lives, there are certain aspects of humans that cannot be perceived by only using these devices. Human actions are, most of the time, unpredictable when analyzed by a random observer. However, trained observers can perceive certain indicators that give them information to classify those actions. These indications are often accompanied by involuntary physiological reactions (e.g., fluctuations in Heart Rate (HR), or an irregular Breathing Rate (BR)). As such, by creating and incorporating sensors that can gather information about those physiological responses in our systems, we are, in turn, moving towards empowering them with the ability to better perceive and understand humans.

Most of the work and effort done towards the development and integration of human-specific sensors has been carried out in the field of wearable sensors. These sensors can be embedded in devices like smartwatches, fitness trackers, clothing, or even placed on the skin as adhesive patches or tattoos. The data collected from wearables can provide valuable insights into an individual's health, well-being, and physical activities [6], [7], [8], [9].

These devices allow for long-term monitoring that, alternatively, would require long-term hospitalizations and/or ambulatory environments that are much more expensive to set up and maintain [10]. This represents a great advance not only in clinical terms but also when it comes to gathering more information about human lives. The success of this type of technology paved the way for the emergence of several commercial solutions (e.g., [11], [12], [13]). Other approaches like Body Sensor Networks or Body Area Networks, have also largely advanced in the last few years, improving medical solutions, the training of professionals (e.g., military, sport athletes), or even other aspects of our daily lives like virtual reality gaming [14], [15]. However, even when considering the advances in the last decade when it comes to miniaturization of devices and wireless technologies, these devices can still be bothersome to use, and most of them require some cooperation from the user.

Despite being around for more than a decade, wearable devices and associated sensing techniques have yet to be explored in real clinical scenarios and have not yet been approved for medical use [16], with even the most recent versions of commercial solutions having considerable measurement error when compared to a straightforward, traditional Electrocardiogram (ECG) [17]. Recent surveys showed that 32% of wearable device users stopped using the device after 6 months, and 50% of users stopped using it after the first year [18]. Additionally, it has also been shown that people that tend to possess and purchase wearable devices are the ones that are already leading a healthy lifestyle [19]. This shows that we still need to explore different approaches to perform long-term monitoring of humans.

One possible solution to cope with these limitations and cooperation issue, is to rely on new unobtrusive techniques that are able to capture these physiological signals without the humans' participation. Therefore, this paper aims to explore unobtrusive sensing, and include it as part of the HiTLCPS process, to extend the range of options in this field. In this context, the contributions of the current paper can be summarized as follows:

1) we propose an architecture for an unobtrusive sensing HiTLCPS system, targeting the healthcare domain;
2) we present the development of a mobile application according to the proposed architecture, for a real-world scenario, namely for assisting elderly people suffering from renal insufficiency;
3) we present an experimental assessment of the developed system, and discuss the obtained performance results.

In this sense, the rest of the paper is organized as follows. Section II presents an overview of the HiTLCPS paradigm, and section III addresses unobtrusive sensing. A case study named *iFriend* is described in Section IV, which implements unobtrusive wireless sensing techniques to gather human physiological data. In section V, we present the results of some preliminary tests exploring the implementation of a wireless sensing technique based on Channel State Information (CSI). Finally, the conclusions and future work proposals are presented in section VI.

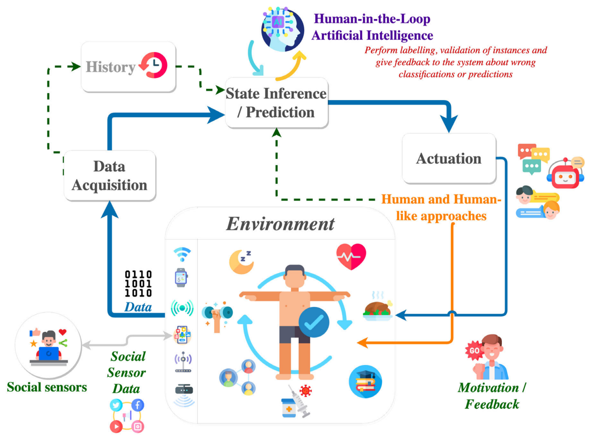


FIGURE 1. **Human-in-the-Loop Cyber-Physical systems model.**

II. HUMAN-IN-THE-LOOP CYBER-PHYSICAL SYSTEMS

The HiTLCPS paradigm is formed by two notions, Human-in-the-Loop (HiTL), and Cyber-Physical Systems (CPS). The former is an area of research gaining growing significance, particularly in relation to systems with critical safety requirements. HiTL refers to a computational model that involves the human-factor. Within these models, humans are consistently involved in the process and, as a result, exert an influence on the outcomes that is challenging, if not impossible, to replicate with absolute precision on every occasion. On the other side, CPSs are a distinct category of systems that amalgamate computational and physical processes. As a result, there exists a reciprocal relationship wherein the physical processes impact the computational processes in a feedback loop. CPSs are already under development and deployment in various domains, including the automotive industry, healthcare devices, military applications, robotics, transportation systems, and building and environmental control sectors.

The primary objective of a HiTLCPS is to possess the ability to understand our intentions, desires, and actions. Rather than humans needing to adjust to technology and acquire the necessary skills to operate it, the technology should adapt to human habits and individuality, eliminating the need for navigating through non-intuitive menus, encountering errors, and dealing with incompatibilities. Figure 1 depicts a HiTLCPS including its three main phases, namely data acquisition phase, the state inference/prediction or state cognition phase, and the actuation phase.

Regarding the data acquisition phase of a control loop, Figure 1 illustrates that there are two primary sources involved: humans and the environment. The environment serves as a significant provider of data that is external to humans but relevant to the system. For example, in a factory monitoring system, the environment encompasses various elements within the factory, including machinery, temperature, air quality, supply chains, and processes, among others. The environment plays a vital role as a data source for any system, as most of the time it is closely tied to the system's performance.

However, most systems that are developed to monitor humans focus mainly on their physical well-being, and ignore their emotional states. A full HiTLCPS should consider both emotions and emotional states of humans. These states are not as easily perceived as the physical ones, especially when considering the use of electronic devices. Humans have studied the psyche and have tried to understand how other humans behave and feel for many centuries, and found several ways to monitor this through well-validated forms and questionnaires. We believe that for HiTLCPS to completely integrate the emotional states of humans, we must integrate human knowledge in the inference and decision-making loop.

For the inference phase, most HiTLCPS systems rely on machine learning models to create predictions about human states and behaviors. Machine learning models have evolved tremendously in recent years, with the advances in technology allowing for the creation of faster and more reliable models. However, most machine learning models are constrained by the amount and quality of data that they have available for training. As such, machine learning systems must rely on humans to overcome these limitations, by applying the concept of Human-in-The-Loop Artificial Intelligence (HiTLAI). HiTLAI refers to the notion of using human knowledge and expertise to perform labelling and validation of instances and give feedback to the system, many times while the system is already deployed, which leads to faster production times for machine learning models and more reliable systems. Additionally, HiTLAI also refers to the use of machine-learning models as decision-helping mechanisms for human-controlled systems, where humans have the final decision about a given operation. We believe, that HiTLAI is also an important factor to address, to create more reliable HiTLCPS systems.

The final phase of any controlled-loop system is the actuation phase, in which the system initiates the necessary adjustments to enhance its performance. In traditional CPSs, actuation may involve tasks like regulating the temperature of a specific chemical process. However, in the context of HiTLCPSs, the actuation extends beyond modifying the system or the environment, as it also includes the actuation performed on humans. This implies that, in HiTLCPSs, the actuation phase encompasses interventions or actions that directly impact human behavior or responses to optimize the overall system performance.

As stated before, humans should interact with the control system in all of its phases and, as such, systems should be designed from the ground up to be intuitive for humans. However, the interaction of systems with humans should also be designed to be as efficient as possible, especially when considering the actuation phase of the control system. For this reason, user feedback should be designed in such a way that it maximizes user acceptance.

It is important to highlight that this paper primarily focuses on the initial two phases of the HiTLCPS concept. The

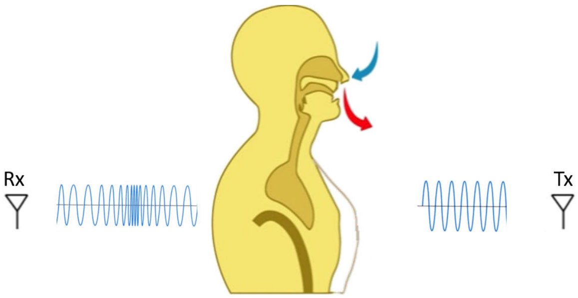


FIGURE 2. Illustrative scheme of the interference phenomena caused by minute movements of the human body on radio frequency signals.

actuation phase and all aspects related to human motivation and feedback are deferred to future research.

III. UNOBTRUSIVE SENSING

In past work, we reviewed existing unobtrusive sensing techniques for humans [20]. In that survey, we proposed a taxonomy for unobtrusive sensing and identified several key approaches. One of those approaches is to use wireless sensing techniques to detect human vital signals by analyzing the interference of the human body in the wireless signals. In this section, we will cover some of those approaches.

Several techniques use artificial signals and the signal-body interference phenomenon to capture humans' physical or emotional states. The human body allows high-frequency signals to pass through it. However, the signal that enters the body is different from the one that leaves it. In Figure 2, we can see a representation of this phenomenon, where the signal that enters the body is modulated by its minute movements. The signals can be attenuated and suffer interference, which affects one or more frequency components. Different signal processing techniques can then be used to detect these changes in frequency.

In [21], the authors leverage this phenomenon by using a single commercial off-the-shelf transmitter-receiver pair to monitor people's respiratory rate, through the interference caused in the Received Signal Strength (RSS). In this work, the authors used a single transmitter node and a single receiver node, where the receiver antenna is also connected to a real-time spectrum analyzer to obtain the baseline. The system was able to achieve a mean absolute error as low as 0.12 breaths per minute. In this work, however, the authors obtained the breathing frequency in the frequency domain using Power Spectral Density (PSD) and, therefore, they were unable to obtain information in the time domain. Furthermore, in instances of time where the subject is moving, breathing estimation cannot be performed. The authors believe that the work can still be enhanced by exploiting channel diversity to improve breathing detection ability.

Additionally, in [21], the authors stated that they were building on the work done in [22], since they believed that by only using two sensors this would reduce the system complexity and increase its feasibility. However, due to the complexity of the system in [22], other sensing opportunities emerge. In this work, in one of the experiments, the authors used a 33-node wireless sensor network to monitor an apartment of 7 by 8 meters. Although the obtained results were less precise than the results in their follow-up work, the use of several nodes allowed them to perform breathing estimation and the location of people in two dimensions. They were able to detect the location of a breathing person with a mean error of 2 meters.

Other authors have also based their approach in the fact that the human body's minute movements interfere with radio signals in a way that is related to vital signs. In one of those studies, the authors proposed the use of off-the-shelf Wi-Fi devices to track human vital signs [23]. In this case, the system is based on the use of the Channel State Information (CSI) of Wi-Fi signals, which is more suitable for this task than RSS-based approaches. The reason behind this is the fact that RSS is already an aggregation of all the sub-carriers' signal strength to mitigate interference in the signal. The sub-carriers are affected differently, depending on their frequency and, as such, there are some sub-carriers that suffer more visible interference caused by human movements. Furthermore, recent comparative studies prove that Wi-Fi CSI measurements provide more robust estimations of breathing rates when compared to other radio frequency measurements [24].

In this work, only one laptop and one Access Point (AP) were used. In a first instance, the CSI data is collected, by using a CSI tool in the laptop [25]. That data is then filtered, and the system runs an algorithm that takes into account moments during which the person moves and moments during which the person is almost static. Similarly, to what happens in the studies that use the interference phenomena to detect human movements, this technique requires the Signal-to-Noise Ratio (SNR) to be high. As such, moments during which the subject moves around or moves a part of the body prevent the detection of the breathing rate and heart rate.

In the mentioned study, the sub-carriers with greater variance in signal strength were selected, as those are the ones that are more affected by the human body in the frequency domain. After the signal is filtered, the signal peaks are detected, for each of the selected sub-carriers. The mean value for the location of each peak in all sub-carriers is computed and the respiration rate estimation is then given by calculating the number of peaks in one minute. In this work, it was also demonstrated that it is possible to detect the respiration rate for two people while sleeping in the same bed, without increasing the number of devices. To achieve this, the authors used the PSD technique. A strong sinusoidal signal, such as the respiration cycle, generates a frequency peak corresponding to the period of the sinusoidal PSD signal. When two people are being monitored, two strong frequency peaks will appear in the PSD, corresponding to the breathing rate of each person. By applying this technique to each of the selected sub-carriers, the authors used the K-means technique to find the two peak clusters that corresponded to the breathing rate of each person.

Using the same approach, it is also possible to detect the heart rate of a person. The movements caused by the heartbeat are smaller than those caused by breathing and, as such, are more difficult to detect. Nevertheless, the heart rate is higher than the breathing rate. This means that, in the frequency domain the heart rate will be represented in higher frequencies than those of the breathing rate and, thus, it is possible to separate both signals. The heart rate also generates a strong sinusoidal signal, which means that the PSD technique can then be applied to find the stronger component in all the sub-carriers' signals. The mean value for all those components can be calculated, which corresponds to the heart rate.

Most of the techniques that use the interference phenomenon are only applied to monitor one or two persons at the same time, as it is difficult to interpret interference without knowing the signal propagation path. The work in [26], however, leverages CSI phase difference data to estimate the breathing rate of several people at once. The proposed system applies tensor decomposition, namely canonical polyadic decomposition, to obtain multi-persons breathing rates. In this study, they demonstrate that, while normal CSI cannot be used to accurately determine the breathing rate of more than two people at the same time with accuracy, the proposed technique can be used to accurately estimate the breathing rate of five people.

The CSI technique can also be leveraged for detecting emotion, as happens in [27], where a system called EmoSense is presented. Contrary to what was done in [28], where unobtrusively sensed physiological signs unobtrusively sensed were used to perform emotion detection, in this work the physical expression of the subject was captured in order to determine emotions, through CSI measurements. There were three major findings for this study: firstly, CSI was indeed able to capture emotional expression; secondly, the performance of the system depends on the experimental setup; and thirdly, the performance is person-dependent.

IV. THE IFRIEND CASE STUDY

As previously stated, perceiving human states is hard due to their unpredictable nature. However, actions and emotions are accompanied by involuntary reactions at the physiological level, namely, subtle changes in the HR and BR signals. As such, the implementation of sensing mechanisms able to monitor changes in these signals are a must for the creation of a full HiTLCPS system.

There are already some pieces of work that explore acquiring these signals in the context of HiTLCPS. However, most of them focus on the use of wearables. Although, wearable technologies have been widely explored and have several advantages when compared to traditional solutions (e.g., ECG), they also have several drawbacks, namely, the lack of validation for medical use, the fact that many of these devices are not accurate and are prone to errors, and the high dropout rate of users. The latter drawback is especially difficult to overcome, as a well-known issue in HiTLCPS systems is the lack of user adoption/participation in the tasks proposed by the system. This could be even more significant when considering a case-study that targets elderly people or people which are not familiar with the use of technology. As stated in [29], one of the open issues of a HiTLCPS system is the implementation of effective sensing techniques that are able to interface with humans in a passive/unobtrusive manner.

In this section, we present the case-study developed for the *iFriend* project, supported by Fundación CSIC, Interreg Portugal-España. This project was developed in partnership between universities from both Portugal and Spain and a Spanish hospital, and included professionals from both the technological field and the medical field. The project objective was the creation of a platform able to monitor elderly people that suffered from renal insufficiency.

Renal insufficiency, can heavily affect the patients' life, and can even lead to death if it not properly treated. For these reasons, patients with this pathology are recommended to keep a healthy lifestyle, which should include moderate physical exercise, regular sleep cycles, and timely taking the prescribed medication. In this project we aimed to create a system that not only was able to track the patients and give detailed information to medical staff, but also helped the patients to keep up with the recommendations from medical staff.

iFriend encompasses all phases of a HiTLCPS system as depicted in Figure 1. However, we give special focus to the use of unobtrusive sensing as a mean to acquire human vital signs data. Additionally, in this system, since it is critical (i.e., it is related to e-Health), actuation mainly consists of direct feedback to the medical team, which can post-process any inference of the system and make decisions.

As presented in [20], there are several approaches to unobtrusive sensing. These approaches are very distinct in their sensing nature. We consider that the one that offered the best solution for our case study is the one based on the detection of vital signals by measuring the interference of the patient bodies with CSI of Wi-Fi signals. In this context, in the next sub-section we provide an overview of the general architecture of the system.

1) THE IFRIEND ARCHITECTURE

iFriend builds on the concepts of HiTLCPS and unobtrusive sensing. As such, the architecture of the system must be able to deal with data from different sources and in different formats. This data heterogeneity led us to choose an underlying platform based on a IoT middleware, namely the FIWARE ecosystem, represented in Figure 3. We have explored the implementation of this backend in [29] and [30], with the exception of configuration and data formats, the

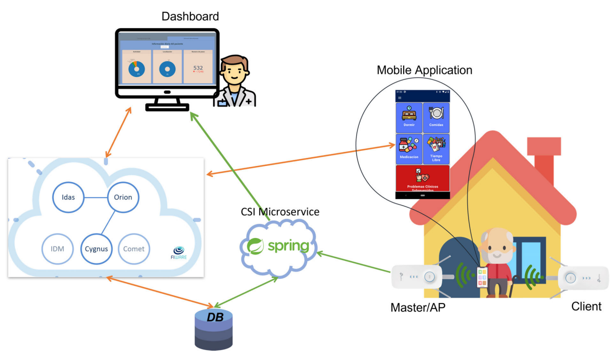


FIGURE 3. ***iFriend* system architecture.**

system implementation is very similar. Thus, we will not address this part of the implementation, that is explained in the mentioned references. The full high-level architecture of the system can be seen in Figure 3.

Additionally, in this system we also have data coming from devices dedicated to unobtrusive sensing, namely acquiring HR and BR from the CSI of the Wi-Fi signals. CSI data has a particular format which is represented by a 3D matrix of $T \times R \times C$, with T being the number of transmitting antennas, R being the number of receiving antennas, and C being the number of sub-carriers of the Wi-Fi signal. Additionally, every matrix cell contains a complex number, which represents the amplitude and phase of each component of the signal.

The device chosen to implement the CSI collection was the TP-Link RE450 [31], which was used to implement the client (transmitting device) and the AP (receiving device). These devices were flashed with the OpenWrt operating system [32], which allowed us to have finer control of these devices and the Atheros CSI tool [33], which was used to transmit and obtain the CSI data. This device used three transmitting antennas and three receiving antennas, and, since we were using the 2.4 GHz band with 20 MHz bandwidth the signal was composed of 56 sub-carriers. As such, every transmitted packet generated a $3 \times 3 \times 56$ matrix of complex components. In addition to the complex format of the data, there was also a large volume of it being generated, since the rate of transmission was 20 packets per second. For that reason, a microservice was created to deal with any data created by these devices, as can be seen in Figure 3 (CSI Microservice). This microservice was implemented with the Spring framework, and mainly served as an interface between the end-devices (AP) and the database. The microservice was also able to serve the dashboard with data queried from the database. It is important to note that we chose to extract the raw data from the CSI measurements, instead of any processed metrics, in order to test and evaluate different models for the prediction of HR and BR.

As can be seen in Figure 3, in addition to the two devices used for collecting the CSI measurements, every patient is also tracked by a mobile device. The mobile application is able to collect passive data (e.g., activity, location, sleep behaviours), as well as data directly provided by the user. We will cover the mobile application in the next section.

Additionally, we can also see in Figure 3, that this system also has a dashboard that is able to give information to the medical staff. Due to the nature of this application, it is important that the decisions in the system are made by someone with expert knowledge of the problem. As we stated before, the inclusion of the humans in the state inference and actuation process is one of the important aspects to address in HiTLCPS, especially so in cases that are of sensitive nature, such as this case study that deals with a medical condition. In this dashboard the medical staff is able to view and analyze the data collected from both types of devices, i.e., smartphone data and HR/BR estimations from the CSI data. It is possible to receive a feed of real-time data, supported by the subscription/notification capabilities of the ORION GE of the FIWARE ecosystem, and it is also possible to analyze the historic data of each patient. In selecting Orion GE of the FIWARE platform for our project, we prioritize its real-time data processing capabilities, seamless integration within the FIWARE ecosystem, and adherence to the NGSI standard for data interchange. And as database we are currently using Mongo DB.

In addition to the mobile application and the devices used to collect CSI, we also used a smartwatch application and a respiration belt [34]. These devices were used to obtain the ground-truth for both the measurements of HR and BR. Both of these devices are connected to the smartphone application and all information is sent and stored through the FIWARE back-end which is hosted in a cloud-based solution within the research centre.

2) THE IFRIEND MOBILE APPLICATION

The mobile application designed for the *iFriend* project followed the same design patterns of the ISABELA other application, presented in [29]. However, some changes were made in order to overcome some drawbacks and tailored the system to the specific case study. The main change was the move from native Android development to the use of the Xamarin framework [35], which is a cross–platform development tool that allows for the creation of mobile applications for both Android and iOS systems that run at native performance. This change was done to address one of the challenges that we faced in past studies, which was the difficulty to obtain subjects for the case studies and to maintain their engagement in the study. By including the iOS platform as a target system of our application we are undoubtedly increasing the number of potential participants of our studies. The second drawback is not directly connected to the use of a single platform, but by obtaining more participants we will be able to better deal with dropouts during ongoing studies. Although the scope of the *iFriend* project encompasses a smaller group of subjects, handpicked to target the particular case–study, the project also aims to present a system that is able to help as many people as possible. As such this was a very important change to our past mobile applications architecture.

Another important aspect that we had to take into account in this project was the User Experience (UX) of the mobile application. As we stated before, HiTLCPSs should take into account human behaviour and be aware of their context. However, systems should also be aware of human restrictions/condition. Since we are targeting a case-study with elderly people, several UX design options had to be made to adapt to the difficulty that elderly people usually have to adapt to technology. We can see some examples of the application in Figure 4.

One of the UX changes we made was the option to use a simplistic layout based on larger images and fewer text. Many smartphones nowadays offer the option to enlarge content to help people with poor sight capabilities. As such, we opted to use the same design pattern for the application. Furthermore, as can be seen in Figure 4a, the navigation of the application was also designed to be minimalist. Figure 4a shows the main page of the application, from which the user can navigate to the available submenus. These submenus include the main daily routines of our subjects, namely their sleep patterns, their meals, their medication, and their leisure time.

When the user selects one of these options, he/she is able to navigate to specific options, as can be seen in Figure 4b. The user can then select the button that corresponds to the action he/she has done. The application then collects the timestamp of that event and sends it to the back-end of the system. In this particular case-study, the medical staff is mostly interested in changes in the behaviour patterns of the user. As such, keeping track of these events and capturing potential changes will help to monitor those changes. Most of the actions covered in the sub-menus are only to be performed once a day (e.g., going to bed, having breakfast, taking morning medication). As it is possible to see in the Figure 4b, once a button is clicked in a sub-menu that option is highlighted with a *check mark* and becomes disabled, to let the user know that the action was performed.

Another option that the users are able to select from the main menu, as can be seen in Figure 4a, is the option to report clinic problems. Keeping track of symptoms of patients with this clinical condition is extremely important, for an effective intervention, since medical staff receive the information at almost real-time in the dashboard, and the patient will not necessarily be required to go to the hospital. As it is possible to see in Figure 4c, the application covers some of the most probable conditions that a patient with renal insufficiency will face. As in previous cases, the application also collects the timestamp of every clinic problem event, as it is not only important to know what problem the user is facing, but also its time and duration.

In addition to the data actively collected by interfacing with the user, the application is also able to passively retrieve data, by using context information and smartphone sensors. Specifically, it is able to collect data on activity, location, connectivity status, step count, accelerometer, gyroscope, proximity sensor values, light sensor values, screen lock status, nearby devices (BLE and Bluetooth), GPS location, application usage metrics and sleep behaviours. Although with this application we moved from an Android native application to a cross-platform application, the Xamarin framework is able to interact with the native libraries of each system and access low-level APIs such as the sensors' API. Furthermore, the iOS operating system offers several counterparts for the API of the Android operating system [36].

In future versions of the application, we aim to also extend the application with a feedback mechanism that is able to give tailored recommendations to each user based on their past behaviour, and also create a direct feedback mechanism from the medical staff to each patient, based on their analysis of each situation.

3) RETRIEVING HR AND BR FROM CSI SIGNALS

In [20], the authors argue that one of the possible approaches to retrieve the vital signals of humans, namely HR and BR, is by analysing the interference caused on the CSI of the Wi-Fi signal when traversing the human body. The work in [23] shows promising results while monitoring up to two people during their sleep, although with some limitations. In the *iFriend* project we aim to implement a solution that offers better performance and solves some of those limitations.

One of the limitations that we aim to solve is hardware dependency, which limits the scalability of this type of solution. Although, the solution in [23] was presented as *"using off-the-shelf Wi-Fi"*, it was implemented by using a CSI tool which only works with the Intel Nic 5300 card [25]. This limits the number of systems which are able to be leveraged as sensing devices. As such, we choose to implement our solution by using the Atheros CSI tool [33], which is, in theory, compatible with any Atheros or Qualcomm device. Furthermore, this library is compatible with both Linux and OpenWrt. OpenWrt is an open-source and largely compatible operating system for Wi-Fi routers and APs, which allows for the deployment of programmable solutions in these devices. In our case-study, we chose to implement our solution by using OpenWrt, since it offers us not only a larger pool of compatible Wi-Fi devices, but also gives control over the transmitting and receiving data. Furthermore, Wi-Fi routers and APs are largely available in most houses, improving the scalability of our solution and making it less expensive.

Additionally, this library allows for the retrieval of more precise information, since it allows for the collection of CSI information not only in the 20MHz bandwidth but also in the 40 MHz, increasing the number of captured sub-carriers from 56 to 114. The library also represents the CSI component values with more precision, since each component is represented with 10 bits for the real part and 10 bits for the imaginary part (while the Intel NIC only offers

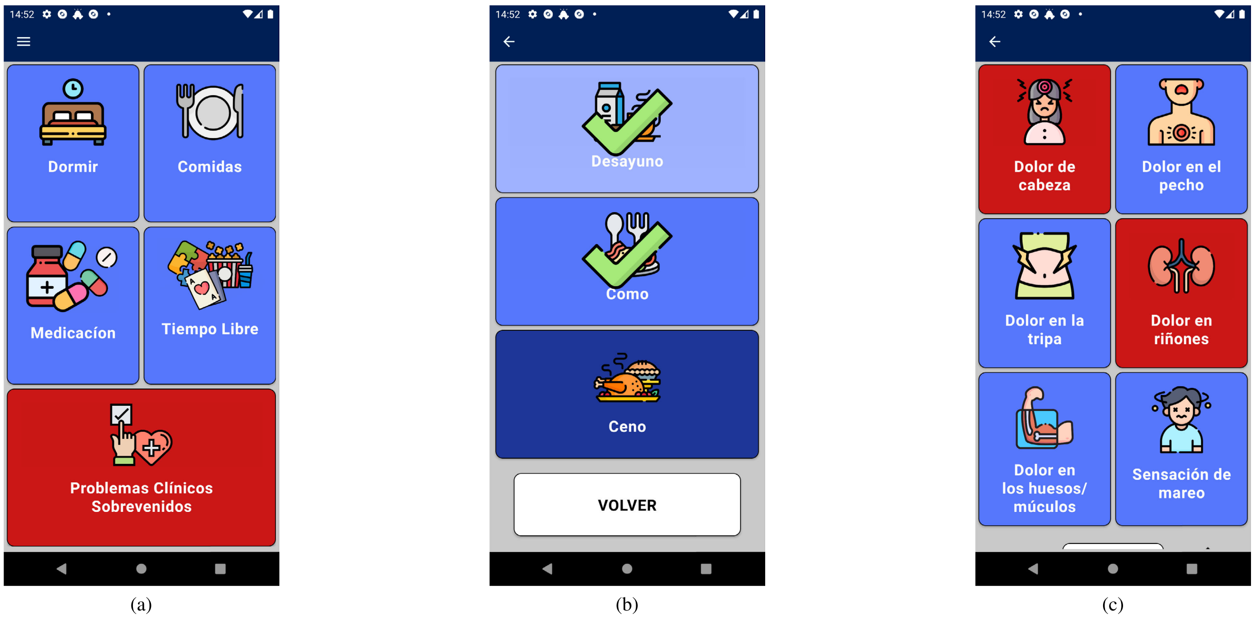


FIGURE 4. ***iFriend's*** **mobile application: Main layout of the application (a); Example of the options available at the** ***"Meals"*** **sub-menu (b);** ***"Clinic problems"*** **sub-menu (c).**

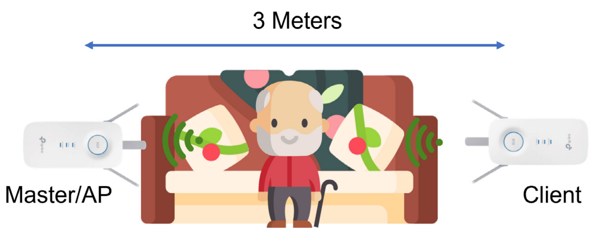


FIGURE 5. Scheme of CSI retrieving using the Wi-Fi Access Point/Client in the ***iFriend*** **system.**

8 bits for each component). This allows for more precision when analysing the retrieved data.

Another aspect that we aim to improve is the scope of the sensing activity, and its limitation in more complex situations. In [23], the authors monitored the HR and BR during sleep. Although sensing while a person is sleeping can give us important information about one's health, and it is one of the sensing opportunities at which sensing can be more precise due to the lower level of movement, we believe that this leaves out several daily periods that can also be very important to monitor. Furthermore, HR and BR decrease to lower levels while people sleep, making it important to validate the performance of this technique during waking time as well.

However, as stated in [20], one of the challenges of this type of technique is the amount of noise during the sensing process, namely caused by larger movements of the body. As such, sensing must be done in static or quasi-static situations. For the case study of the *iFriend* project, we propose the situation depicted in Figure 5. As can be seen in the figure, we propose that sensing is performed during the time that the subject sits. The medical staff that advises the project believes that this is where the subjects spend most of their day, either watching tv, reading, or on their mobile devices (smartphones/tablets).

As can be seen in Figure 5, sensing is performed using two identical devices, namely the TP-link RE450. These are inexpensive devices that can be flashed with a custom OpenWrt firmware, and allow us to develop code to be run on them. One of the devices acts as an AP, broadcasting a Wi-Fi network, while the second acts as a client that connects to the Wi-Fi network and periodically sends packets.

In the context of this case study, we performed some preliminary test, and the results described below.

V. EXPERIMENTAL ASSESSMENT AND RESULTS

In the *iFriend* project we aim to monitor elderly people with kidney insufficiency, by using both data collected from smartphones and Wi-Fi CSI. In the first phase of the project we focus on the collection of data, from trial subjects, to be then processed and worked on to generate models able to determine HR and BR. As such, in this section, we will only present preliminary results of small trials performed in a laboratory set up.

As we previously stated, we implemented the *iFriend* prototype by using the Atheros CSI tool [33]. This tool allows us to gather CSI, which normally is not available in off-the-shelf devices. The tool is also compatible with any Atheros and Qualcomm device, and can be compiled for both Linux-based systems and OpenWrt. As such, it can be used in the vast majority of APs available in the market, pending the installation of the OpenWrt operating system. We chose to implement the prototype by using two identical devices, namely the TP-Link Re450. Since these devices use a different architecture, namely the *mips_24kc*, we performed

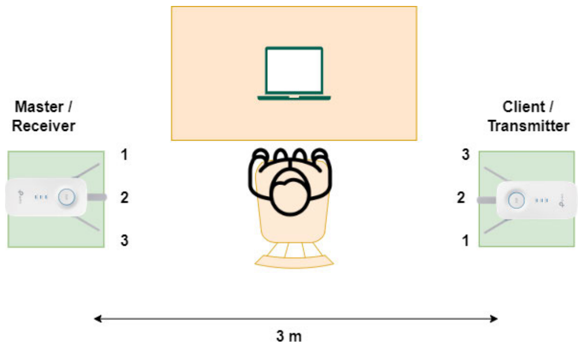


FIGURE 6. Representation of the experimental setup for the collection of Wi-Fi CSI data.

a cross-compilation of the tool and created a compatible firmware image, which was then installed on both devices.

Additionally, one of the devices was set up as an AP/Primary, which was sharing a dedicated Wi-Fi network, and the other one was set up as a client of that network. The network was shared using the 2.4GHz band and with a bandwidth of 20MHz. The primary was also connected to a different network to send the received packets to the server for storage. We choose to use another network, in this case, one connected by the ethernet interface of the device, so no additional interference was generated in the signal by additional transmissions.

A scheme of the experimental setup can be seen in Figure 6. As can be seen in the figure, it resembles the intended scenario in which the prototype will be used (Figure 5), that is, monitoring elderly people while they are watching tv and/or sitting on the couch. In this experimental setup, we choose the scenario of someone working on their laptop. The subject was sitting on a chair next to the table with his laptop on it.

Additional, considerations were also made in terms of the positioning of the devices. Namely, the devices were set at a distance of 3 meters from each other to correspond to the expected scenario for the real-world trials, and they were at a height of roughly 85 cm, to be at the level of the chest area.

Both of these scenarios are more challenging than the ones found in the reviewed literature, which target the monitoring of people during their sleep [23], since there are additional movements from people. One of the challenges of this type of monitoring is the fact that large movements from the human body (e.g., rapidly moving your arms, sitting movement, standing up) generate larger CSI interference, which, in turn, makes it harder for signal processing techniques to identify interference data generated by the HR or BR.

In Figure 7 we can see the amplitude of a sub-carrier in the CSI. The figure also denotes an interval in time when movements from the subject occur, marked as red. As can be seen in the figure, larger movements cause interference both in terms of amplitude and frequency, thus making it harder for the algorithms to estimate HR and BR.

Lastly, in addition to the previously explained setup for the collection of CSI, two additional devices were used for determining the HR and BR ground truth. For HR, the Tic Watch S2 smartwatch was used to collect ground truth values [37]. This device runs the Android Wear OS and, as such, it is programmable. A small application was developed to collect the HR values and send them to the *iFriend* server. For the BR ground truth values, the Go Direct respiration Belt was used [34]. This device is attached to the chest with a strap belt and can measure the respiration rate based on the chest's movements. It also offers an API, and two communication possibilities, by USB connection or by Bluetooth. By trial and error, we found that the Bluetooth interface generated interference with the Wi-Fi signal because of the proximity of the devices and, thus, we chose to use the USB connection.

A. HEART RATE AND BREATHING RATE ESTIMATION

CSI is the channel attribute of each communication link. It describes how much each signal transmission path was weakened, by factors such as power decay over distance, scattering, multipath fading, shadowing fading, and others. CSI is used to adapt the communication system to the current channel conditions, increasing the reliability, in multi-antenna systems, also known as MIMO. Channel information can be modelled in the frequency domain as:

$$\overrightarrow{Y} = H\overrightarrow{X} + \overrightarrow{N} \tag{1}$$

where $\overrightarrow{X}$ and $\overrightarrow{Y}$ represent the transmitted and received signal vectors, respectively. $\overrightarrow{N}$ represents the Gaussian noise vector and the H matrix represents the channel's frequency response. The CSI of all sub-carriers can be estimated by the following formula:

$$H = \frac{\overrightarrow{Y}}{\overrightarrow{X}} \tag{2}$$

MIMO systems have multiple receiving and transmitting antennas, as such for each sub-carrier the CSI matrix has a component for each pair of antennas. The matrix of the n $^{\text{th}}$ sub-carrier, with r receiving antennas and t transmitting antennas can be expressed, as follows

$$H_n = \begin{bmatrix} h_{11} & h_{12} & \dots & h_{1r} \\ h_{21} & h_{22} & \dots & h_{2r} \\ \vdots & \vdots & & \vdots \\ h_{t1} & h_{t2} & \dots & h_{tr} \end{bmatrix} \tag{3}$$

As stated before, in the tests performed we used the 2.4GHz band and a bandwidth of 20MHz, which means the signal had 56 sub-carriers. Additionally, the used devices had 3 antennas each (3 receiving antennas and 3 transmitting antennas). Therefore, for each packet sent we obtained 56 matrices of 3×3 each. Since we only need one stream, we choose to use the pair of antennas $r = 3$ and $t = 1$, which as can be seen from Figure 5, is the one that has the more direct path through the human body.

Additionally, each component of the sub-carriers matrix is represented as a complex number, which represents the

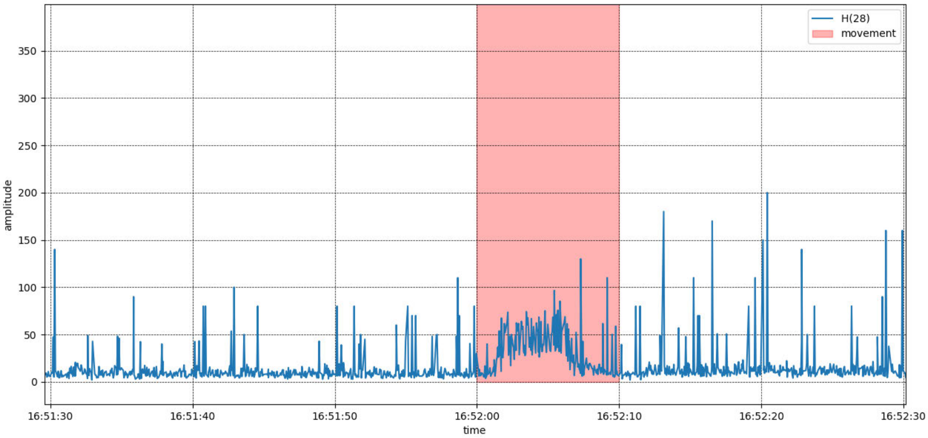


FIGURE 7. Example of interference generated by movement in the CSI signal.

TABLE 1. CSI HR estimation error relative to ground-truth, in beats per minute.

	Max Abs Error	*Min Abs Error*	*Mean Abs Error*
1 min window	17.12	0.08	7.32
2 min window	15.57	0.06	5.86
3 min window	18.05	0.12	6.33
1 min w/ movements filtered	13.93	0.08	5.65

TABLE 2. CSI BR estimation error relative to ground-truth, in breaths per minute.

	Max Abs Error	*Min Abs Error*	*Mean Abs Error*
1 min window	8.36	0.09	1.71
2 min window	7.82	0.28	1.59
3 min window	4.32	0.00	1.24

amplitude and phase of the signal. In our tests, we used only the amplitude information of the signal. Unless indicated otherwise, from this point on when referring to the components of the CSI matrix we are referring to the amplitude.

For these preliminary trials, we used a packet rate of 20 packets per second and the algorithms described in [23]. For the detection of the HR, we first converted the signal to the frequency domain and then applied a band-pass filter to remove any frequencies outside the normal HR frequencies during a rest period. That is, any frequency below 0.9 Hz (54 beats per minute) and frequencies over 2 Hz (120 beats per minute). Secondly, the PSD was calculated for each sub-carrier, and the mean PSD of all sub-carriers was also calculated. The HR estimation was then found by finding the max frequency component of the mean PSD of all sub-carriers.

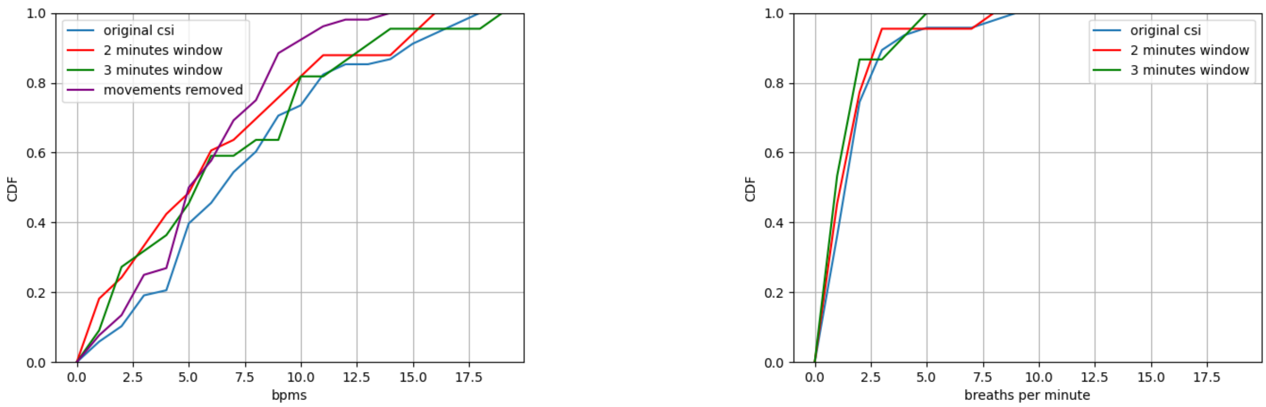
A collection of data of one and a half hours was performed with the subject using the smartwatch for ground-truth. We also compared the results using different time windows, that is, the CSI signal was divided into different windows of time with the same duration, and the estimation was made for each individual window. The smartwatch retrieved a value for the heart rate every minute, and for larger windows of time the mean value was calculated.

The values for maximum, minimum and mean absolute error of the HR estimations can be seen in Table 1. We performed estimation tests for windows of 1 minute, 2 minutes and 3 minutes. Additionally, we present the results for 1 minute windows when removing instances of time that could correspond to the movement of the subject. The largest mean absolute error was for the 1-minute window, with 7 beats per minute. It is also possible to see that the minimum absolute error for all the approaches is near 0. However, the maximum absolute error value is larger than 13 beats per minute for all tested approaches. As can be seen from the presented values, changing the window size results only in small differences, showing that this is not the most important factor to consider.

We believe that the larger error values are due to instances in time when the subject was significantly moving. The data was manually annotated and 1-minute windows were removed for any instance that resembled the phenomenon shown in 7. It is possible to see in Table 1, that removing these problematic instances in time produces better estimations.

In Figure 8a, we present the cumulative distribution function (CDF) plot for all the above approaches. Notably, our analysis reveals that while approximately 50% of the results exhibit errors below 5 beats per minute across various methods, the presence of movement significantly impacts accuracy. Specifically, when excluding instances of movement, we observe that 90% of estimations achieve errors below 10 beats per minute. However, it's essential to acknowledge that these results indicate significant deviation from the ground-truth data obtained from the smartwatch. We recognize the existence of errors in our HR estimation approach, and we plan to address these limitations in the future iteration of this work.

Concerning the BR estimation, similar acquisition sessions of one and a half hours were performed, with the subject using the GoDirect Respiration belt. The same packet rate of 20 packets per second was also used for this acquisition. The algorithm for the estimation of the BR is very different



(a) HR (b) BR

FIGURE 8. CDF for HR and BR estimations.

from the one used for the HR, since it is based on the time domain instead of the frequency domain. Firstly, the *Hampel* filter is used to remove any outliers of the signal. Secondly, a moving average filter is used to smooth the signal. We then find the peaks of the signal and remove any fake peaks. Lastly, the breathing rate for a sub-carrier is estimated from the number of peaks per minute. The final breathing rate estimation is obtained by calculating a weighted mean based on the variance of any sub-carrier, since the sub-carriers with larger variances are more affected by the movements of the body.

The values for maximum, minimum and mean absolute error of the BR estimations can be seen in Table 2. Again, we performed estimation tests for windows of 1 minute, 2 minutes and 3 minutes. All approaches had a mean estimation error below 2 breaths per minute. Furthermore, increasing the duration of the time window for estimation lowers the mean absolute error of the estimation. It is also possible to see that, for all approaches, the minimum error obtained was near 0. However, the maximum absolute error even in the 3-minute window approach is above 4 breaths per minute.

In Figure 8b we present the CDF for the BR estimations. In this figure, it is possible to see that for all approaches, 80% of the estimations had an error of below 2.5 breaths per minute. Additionally, for the 2-minute windows case, 90% of estimation errors are below 3 breaths per minute. Although these results are promising, we believe that there is still room for improvement.

As happened for the HR estimations, we believe that the larger errors are due to instances of time when the subject performed larger movements. In future work, we will improve the algorithms used to filter these instances and perform opportunistic sensing when the subject is quasi-static.

VI. CONCLUSION AND FUTURE WORK

In this paper, we proposed an architecture for a HiTLCPS system that targets the healthcare domain. The proposed system maximizes human interaction and participation, and explores recent technologies to make it as unobtrusive as possible. The ideas behind this model are, on one side, to support the development of IoT-based monitoring systems that are useful to human beings, improving their quality of life and, on the other side, to make the use of these systems as intuitive and natural as possible.

The *iFriend* case study targeted health monitoring of elderly patients with specific pathologies. This study explored the use of unobtrusive wireless sensing to gather vital signs data, with the purpose of minimizing the impact of the system on the monitored patients.

In this paper we focused on some preliminary results for the wireless sensing implementation used in the *iFriend* project. The obtained results point to the feasibility and usefulness of unobtrusive wireless sensing techniques, proving their usefulness in the data acquisition components of HiTLCPS systems. This topic will be additionally explored in future work.

In our future work, we are committed to conduct comprehensive comparative studies involving the simultaneous measurement of parameters using our proposed method and established medical equipment. These studies will include diverse populations, spanning different age groups and stress levels, to ensure the generalizability and robustness of our findings.

Lastly, we highlight that privacy is one of the main concerns when building this type of systems. Human-related data is very sensitive, and humans themselves are increasingly becoming aware of that. This creates several constraints for HiTLCPSs, as we need to maintain a trade-off between the usability of the system and its privacy [38]. Furthermore, when we add new sensing capabilities, such as wireless sensing, we create new privacy concerns, such as having techniques that can collect human-related data even through walls and without user knowledge. Addressing these concerns, by studying, developing, deploying, and integrating privacy-aware models and privacy-preserving mechanisms, is one of the most important future work directions.

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