Remote Health Monitoring System for the Elderly based on mobile computing and IoT

Rafael Cardoso
Instituto de Telecomunicações
Instituto Universitário de Lisboa (ISCTE)
Lisbon, Portugal
rscoa@iscte-iul.pt

Octavian Postolache
Instituto de Telecomunicações
Instituto Universitário de Lisboa (ISCTE)
Lisbon, Portugal
opostolache@lx.it.pt

Carlos Coutinho
Instituto Universitário de Lisboa
(ISCTE), ISTAR
Lisbon, Portugal
carlos.eduardo.coutinho@iscte-iul.pt

***Abstract*—Due to the increasing technological innovation over the last decades, the average life expectancy of a human being has been increasing exponentially. Although this is an excellent step forward for humanity, it has led older population to being more prone to illness, making them more vulnerable to accidents such as falls. In this article a study is made on the existing literature in non-intrusive remote health monitoring systems, towards the design and implementation of an IoT system capable of identifying fall situations and monitor cardiac data. A Systematic Literature Review (SLR) method was considered in this work, focused on reviewing the existing literature on remote health monitoring systems, having fall detection algorithms, based in IoT. The Design Science Research (DSR) methodology was used to seek to enhance technology and science knowledge about this paper's topic, through the creation of an innovative artifact.**

The system includes a smart watch (Lily-Go T-Watch-2020 V2), programmable in C under Arduino IDE to detect falls and a photoplethysmography monitoring unit (PPG) based on a Onyx 9560 Bluetooth oximeter, capable of measuring the user's blood oxygen percentage (SpO2) and heart rate, in real time. It also provides remote monitoring through a user-friendly website to visualize live data about the status of the user. The system was tested in volunteers to show the effectiveness of remote health monitoring systems for the elderly population.

***Index Terms*—Health Monitoring, Fall Detection, PPG, DSR, SLR**

I. INTRODUCTION

With the significant increase in new technologies starting in the middle of the 20th century, the average life expectancy has increased exponentially, as shown in Fig. 1, reaching an impressive figure of 79 years in 2019 [1]. The increase in average life expectancy raises a new problem. The elderly population is increasingly exposed to disease and health threatening events such as falls. This is called frailty, which is a measure of vulnerability that comes as a consequence of cumulative decline in many physiological systems during a lifetime [2]. The increased frailty of elderly people leads to a relatively poorer quality of life in terms of health, because despite living longer, they live with many more health problems. Quality of life is a very subjective topic. Not only does it involve health, but is also influenced by family life, social and financial status, friends and many others. However, a study of older people over 80 years old, indicates that

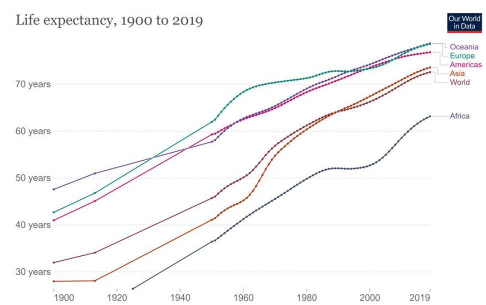

Fig. 1: Average life expectancy through the years [1]

for 96% of the older people who indicated that they had a poor quality of life, health is a determining factor in their quality of life [3]. Therefore, it is necessary to innovate and create technologies that not only increase the average life expectancy but also provide a higher quality of life for the elderly by monitoring their health-related physiological data. This innovation is based on the growing area of IoT where the number of IoT devices has been increasing over the years. One projection made indicates a growth from 8 billion devices in 2017, to 20 billion devices in 2020 [4]. The applications for IoT are endless and exist in all areas of our daily lives, not only in healthcare. Some examples of the areas are agriculture, automotive, telecommunication, industry, among many others [5]. It is necessary to provide the older population with tools that not only allow them to live longer, but also to live with more quality of life, detecting unexpected accidents and monitoring health related data that can anticipate diseases. These tools must be based on IoT because it is the present and the future of technology, and thus improve the living conditions of the elderly, health wise.

The goal of this article is to create a non-intrusive remote health monitoring system, based on Internet of Things (IoT) sensors, capable of monitoring the living conditions of the elderly and in cases of life-threatening danger send warnings to the proper authorities, possibly saving lives. The diagram of the expected system architecture can be seen in Fig. 2.

This paper will focus on creating a system capable of:

- Identifying falling situations for the user by accessing

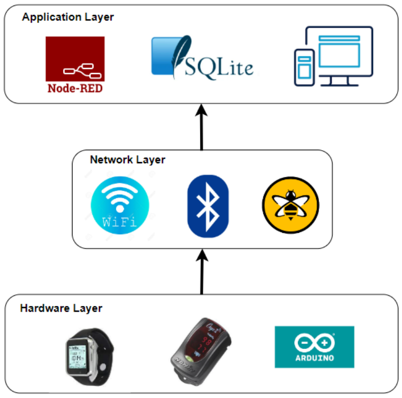

Fig. 2: Remote monitor system architecture

the accelerometer sensor on the Lily-Go T-Watch-2020 V2 smart watch;

- Measure SpO2 and heart rate data of the user, using a Onyx 9560 oximeter, displaying the values on the Lily-Go T-Watch-2020 V2 smart watch via Bluetooth communication, through Node-Red;
- Able to locate the user through GPS location on the watch, in cases of medical emergency;
- Processing the data in the cloud, store the data in an SQLite database and provide a user-friendly visualization website;
- Sending warnings to health entities in the mentioned emergencies.

This work was carried out using the facilities of the ISCTE-IUL Campus and used hardware provided by the Iscte School of Technology and Architecture (ISTA).

II. Related Work & Methodology

This chapter reviews the literature beneficial to this paper. It provides a good technical knowledge and starting bases for the realization of the necessary work.

For a focused and organized research, a systematic review of the related work encountered was defined. Then, the focus was on reviewing existing literature on remote health monitoring systems.

To analyze and understand the related work already done in the field of this paper, the Systematic Literature Review (SLR) method was used. In health care, systematic reviews and meta-analyses have become increasingly relevant [6]. Therefore, to gain a better insight into the area of remote health monitoring, this research method was conducted on the available literature.

To conduct an SLR, it is necessary to define a main search database. The database for this work was the Scopus tool. In the need, to acquire additional information for the literature review, a secondary database, provided by Google, called Google Scholar, was used.

The search in the Scopus tool was performed through a query, while in the Google Scholar tool the search was only performed when necessary, through keywords. The query run was initially: ”(health AND remote AND monitor AND systems)”. This query proved to be too generic as the number of related papers found was 2234. With such a high number, it is impossible to make a SLR of this magnitude individually.

So, to highlight the most relevant works among the enormous number of results obtained, some Inclusion Criteria (IC) and Exclusive Criteria (EC) were defined. These criteria are found in Table 1.

Including	**Exclusive**	**Number of related papers**
All open access	Not being open access	610
From 2014 onwards	Older than 2014	511
In the area of Computer Science, Engineering and Medicine	Not in the area of Computer Science, Engineering and Medicine	415
Written in English or Portuguese	Written in other than Portuguese or English	413
Document type: Article	Not an Article	298

TABLE I: Inclusion and Exclusion criteria defined in the search for related work.

Even with the ICs and ECs defined, there were still a substantially large number of related articles. So, the authors applied an additional exclusive criterion that removes articles related only to medicine. This leaves us with 137 articles. The next step to slim down this number is to skim through the abstract of the remaining articles and select those that appear to be more relevant to the work to be carried out.

After this step there were 55 articles left, which were then analyzed for the next subsection, reviewing how monitoring systems are developed.

Fall detection systems are an important kind of monitoring devices, particularly for the elderly population, where falls can have serious health effects. Main challenge fall detection systems face is differentiating a fall from activities of daily living.

The work carried out by [7] concludes that current fall detection research is hampered by several flaws. The fact that simulated fall scenarios are only performed by young healthy volunteers, the fact that simulated falls do not always represent real fall situations and the fact that falls are usually performed onto thick mats that provide a cushioning effect and change the characteristics of the fall impact from that of a real fall are some of these shortcomings.

In the work carried out by [8], the fall detection system, uses a threshold-based fall detection algorithm. The first feature to define the event of a fall, is defining the threshold of the sum acceleration and rotation angle information. When an actual fall occurs, the impact of the human body with the ground produces a visible peak in the cumulative acceleration, which can be determined by the equation:

$$|a| = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{1}$$

Where a_x, a_y and a_z represent each axis acceleration of the accelerometer. This magnitude is the first step to distinguish high intensity movements from others. However, high intensity activities, like jumping, also produce peak values, which mean that additional detection features are required.

The second feature is an angle calculated based on acceleration measurements. By separating the gravity components before and after a human fall, then it is possible to calculate the rotation angle of accelerometer coordinate in 3D space, which is also equivalent to the rotation angle of the gravity vector relative to the fixed coordinate.

This work concludes that normal activity of resting also has similar rotation as falling and it may trigger false falling alarms. The correct definition of the parameter $a_{threshold}$, is the most important factor to distinguish falling from lying down. It also concludes that it is important to experiment with a group of people who are more differentiated in terms of age, gender, and weight, in order to improve the reliability and robustness of the threshold.

Within the scope of the topic under study, the research questions that motivate the analysis and subsequent response are the following:

1) How can a non-intrusive health remote monitor system influence the health of an older patient?
2) How does the system improve the quality of life of the elderly?
3) How to design the system so that the response to an emergency is robust and effective?

With these research questions, this work aims to innovate in remote health monitoring, especially in the area of elderly health.

This work also defined a set of hypothesis to be proposed to reply to each research question. Each hypothesis comprises a prediction about how two or more variables will interact. It's like making an educated guess about what will happen in an experiment [9].

- **Hypothesis 1:** By being a system capable of detecting falls, monitor cardiac data and able to send warnings to caregivers or even in extreme cases to authorities in cases of medical emergencies, the patient will directly benefit from better health over time and quick responses in cases of distress.
- **Hypothesis 2:** As seen in the previous subsections, health is the determining factor in quality of life, for the older population. By improving their health conditions, their quality of life is directly improving as well.
- **Hypothesis 3:** The system needs to be user-friendly to be perceptible to the average caretaker, capable of rapid response to emergencies by having low latency levels and needs to be a robust system in case of power failures, hardware failures, among other unforeseen events.

In this paper, the research process based on Design Science Research (DSR) was followed. DSR is a problem-solving paradigm that aims to improve human knowledge through the creation of novel products. Simply said, DSR aims to improve technology and science knowledge bases by developing new artifacts that solve problems while also improving the environment in which they are implemented [10].

The first step begins with identifying and defining the research problem as well as justifying the value of a solution. Then, defining the objective for that solution is the second step. After that, in the third step, the design and development of the artifact is done, by determining the artifact's desired functionality and its architecture. The fourth step consists in demonstrating the use of the artifact to solve instances of the research problem. Afterwards, in the fifth step, an evaluation of the solution is made, based on a comparison of the goals and the actual results obtained through the use of the artifact. Lastly, all aspects of the problem and the designed artifact are communicated to the relevant stakeholders, being other researchers or other relevant audiences, like professionals on the same area of work.

The DSR process also includes four different entry points [11]: **The problem centered approach**, starting in step one, for research where the concept came from observing the situation or through a report from a previous project that proposed future research. **The objective-centered solution**, starting in step two, mostly for research that needs to develop an artifact. **The design and development-centered approach**, starting in step three, being suitable for situations where the artifact already exists, but needs further developments. **The client/context initiated solution**, starting in step four, for research based on observing a practical solution that has worked.

In this work, the DSR model was applied using the problem centered approach due to the fact that the addressed problem is already known.

III. System Description

A. Hardware

The hardware used in this system was the LILYGO T-WATCH-2020 V2 and the Onyx 9560 oximeter.

The LILYGO T-WATCH-2020 V2 is based on a design concept that can be interacted with, networked, programmed, and worn. It incorporates Wi-Fi/Bluetooth, which is more convenient to connect to the Internet and is simple to program and build, with ESP32. The big difference from V1 to V2 is the addition of the GPS function and the ability to store data on a memory card.

The Onyx 9560 is a pulse and blood oxygen saturation monitoring device, designed for individuals who desire a Bluetooth oximeter, allowing them to upload measurements to their phone or digital device. It also offers a range of up to 100 meters, and allows the user mobility during use, unlike many other oximeters.

B. Software

The Arduino Integrated Development Environment - or Arduino Software (IDE) - is a free software that contains a text editor for writing code, a message area, a text console, a toolbar with buttons for common functions and a series of menus. It connects to the microcontroller hardware to upload programs and communicate with them. This is the software we use to program the LILYGO T-WATCH-2020 V2.

Node-RED is a programming tool for connecting hardware devices, APIs and online services. Node-RED is built on Node.js, taking full advantage of its event-driven, non-blocking model. This makes it ideal to run at the edge of the network on low-cost hardware. This is where all system components are connected and communicate with each other and the database, via Wi-Fi using the MQTT protocol and via Bluetooth in the oximeter case.

SQLite is an open-source SQL database that stores data to a text file on a device. One of SQLite's greatest advantages is that it can run nearly anywhere. Its flexibility and the fact that it is better prepared to deal with a smaller flow of data, was the decisive factor in choosing it as a database.

HTML stands for HyperText Markup Language. It is a standard markup language for web page creation. It allows the creation and structure of sections, paragraphs, and links using HTML elements (the building blocks of a web page) such as tags and attributes. HTML is used for web development, Internet navigation and web documentation.

C. System Overview

The system was designed to detect possible cases of falling using the accelerometer sensor embedded in the smartwatch. A fall detection algorithm, designed in the Arduino IDE using C programming language was also considered.

The fall identification algorithm has two fall detection factors. The first is comparing the acceleration (Acc) calculated with the linear acceleration per accelerometer axis (X, Y and Z), with a predefined maximum acceleration limit (a_{th}), which is tested in the next chapter of this work, to obtain the value with the highest hit percentage, in the detection of true falls.

The second factor helps a lot in detecting false positives and is implemented in the touchscreen interface of the smart watch. If the user does not click a button in the touchscreen interface, indicating that it was a false fall alarm in a period of time after the detection, a possible fall is confirmed, and the alarm for the caregivers will be sent.

The system also has the ability to collect heart rate and SpO2 data using an Onix 9560 oximeter. The device communicates with the Node-RED platform via Bluetooth, which forwards messages to the smartwatch via the MQTT protocol, publishing the heart rate values to the "/BpM" topic and publishing the blood oxygen saturation values to the "/Spo2" topic.

Node-RED stores all the data collected in an SQLite database. The website, coded using HTML and PHP, is used to visualize this data in a user friendly and objective way.

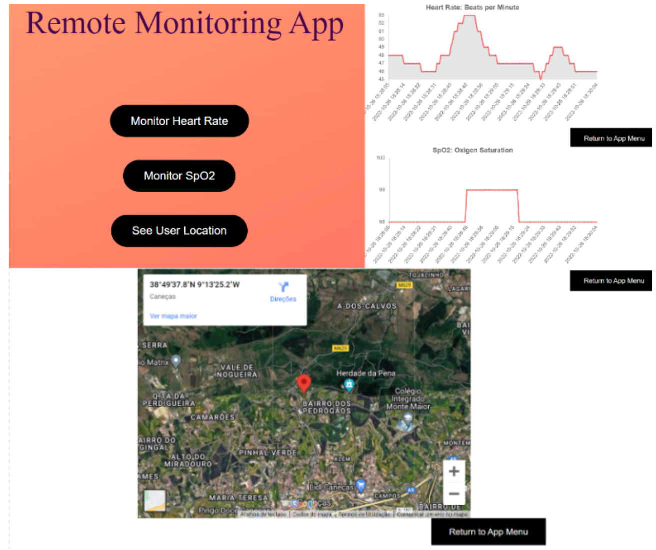

Fig. 3: System visualization (Website) - Heart Rate, SpO2 and current GPS location of the user

Fig. 4: Lilygo T-watch-2020 v2 - final display

The system also has the possibility to display the real-time location of the user, using GPS coordinates obtained from the smart watch, stored in the database.

Fig.3 presents the visualization of the collected data via the website created. Thus, the website offers 3 options for visualization. The page "Monitor Heart Rate" presents the user's heartbeat, while the "Monitor SpO2" page shows the blood oxygen saturation values. Finally, the "See User Location" page shows the current location of the user of the system.

Fig. 4 displays the visualization through the watch, showing not only the date and time, but also showing the heart rate and SpO2 data, if the user is measuring them through the oximeter. The watch also features a bar that shows how intense the movement is and a button that, given a possible fall, the user can click to confirm the false positive.

IV. Results and Discussions

To validate the system, several different types of simulated falls were tested, using a thin-width mattress as a landing platform. The tests were made on three volunteers, two men

Type of Fall	False Negatives	True Positives
Forward	13,3%	86,7%
Sideways to the Left	43,3%	56,7%
Sideways to the Right	26,7%	73,3%
Backward	28,3%	71,7%

TABLE II: Types of falls: (a_{th}) = 70%:

Type of Fall	False Negatives	True Positives
Forward	53,3%	46,7%
Sideways to the Left	81,7%	18,3%
Sideways to the Right	73,3%	26,7%
Backward	71,7%	28,3%

TABLE III: Types of falls: (a_{th}) = 84%:

and one woman (23-year-old M, 62- year-old M, and a 59-year F). Forward falls, sideways falls, and backward falls as if it were a slide, were simulated onto the mattress. Each type of fall was executed 20 times by each volunteer of the test.

The other type of tests performed, focused on activities of daily living (ADL) such as walking, running at different speeds, and vertical jumping. During these tests, cardiac data monitoring was also done to validate the proper functioning of the system.

In the first test a maximum acceleration limit (a_{th}) of 70% was used. First the acceleration values obtained with the accelerometer are transformed to be between 0 and 100, where 0 is no acceleration and 100 is maximum acceleration. By testing with several different values of (a_{th}), the most correct value to serve as the maximum acceleration limit can be estimated, thus maximizing the accuracy of the fall detection algorithm.

In the second test the system was faced with cases of false positives results in various day-to-day activities (ADL), like walking, running, and jumping.

In the first test it is observed that when evaluating possible falls, the limiting factor of maximum acceleration has a great impact on the correct detection of a possible fall.

For an a_{th} = 70%, most of the fall events are correctly detected, which is the main goal of the system. Increasing a_{th}, many of the possible falls go unnoticed.

Analyzing these tables, the authors concluded that frontal drops are the most easily detected by the algorithm, so they do not depend so much on a_{th}.

Type of ADL	False Positives	True Negatives
Walk	0%	100%
Run - Slow Pace	0%	100%
Run - Medium Pace	40%	60%
Run - Fast Pace	93,3%	6,7%
Jumping	10%	90%

TABLE IV: Types of ADL's: (a_{th}) = 70%:

Type of ADL	False Positives	True Negatives
Walk	0%	100%
Run - Slow Pace	0%	100%
Run - Medium Pace	0%	100%
Run - Fast Pace	36,6%	63,3%
Jump	0%	100%

TABLE V: Types of ADL's: (a_{th}) = 84%:

The side falls tests show that falls to the side where the user places the watch are less easily detected.

In the second test, as expected, for a larger a_{th}, fewer false positives are detected by the system.

For an a_{th} of 70%, fast-paced activities were detected as falls most of the time. As the system is designed for elderly users, the focus becomes more on detecting possible falls and minimizing possible undetected falls.

To test the proper functioning of the remote monitoring of cardiac data, the tests to the different ADL's were performed, using the oximeter on the right index finger, to observe the evolution of the heartbeat during the tests.

In the graph seen in Fig. 6, the change in heart rate and SpO2 values over the course of a 20-second run, with a subsequent 40 seconds of rest, is shown, for the 3 different running intensities tested.

By analyzing Fig.6, it is visible the expected increase in heart rate at the moment of the run ([0,20] seconds), and the consequent slowing down of the heart rate in the following 40 seconds as a consequence of the resting moment. It is also noted that the SpO2 values tend to decrease during the physical activity (first 20 seconds), although these changes are not very noticeable because of the short duration of the run. The results show that the system can indeed detect falling situations and monitor cardiac data when the oximeter is in the user's finger. However, the limitations of the fall detection algorithm are important in the final definition of the system's performance. The biggest limitation is the fact that it is impossible to recreate real fall situations in a human being. The testing of falls assumes that the tester knows he is going to simulate it, so it won't be close to what a real fall would be, since these are always unexpected.

Another limitation of the testing is that the tests were not performed for every type of possible user of the system. It is practically impossible to cover all the possible characteristics of the possible users of the system, whether they are users with reduced mobility, users with other types of conditions that involve abrupt arm movements, leading to false detection of falls, among other examples.

The system proves to be quite capable of identifying cases of falls and due to the second false alarm confirmation factor, the user can trigger the system in cases of false detections, to avoid false alarms to the caregivers.

Taking this second factor into account, a a_{th} of 70% was selected as the best acceleration threshold value, as the system

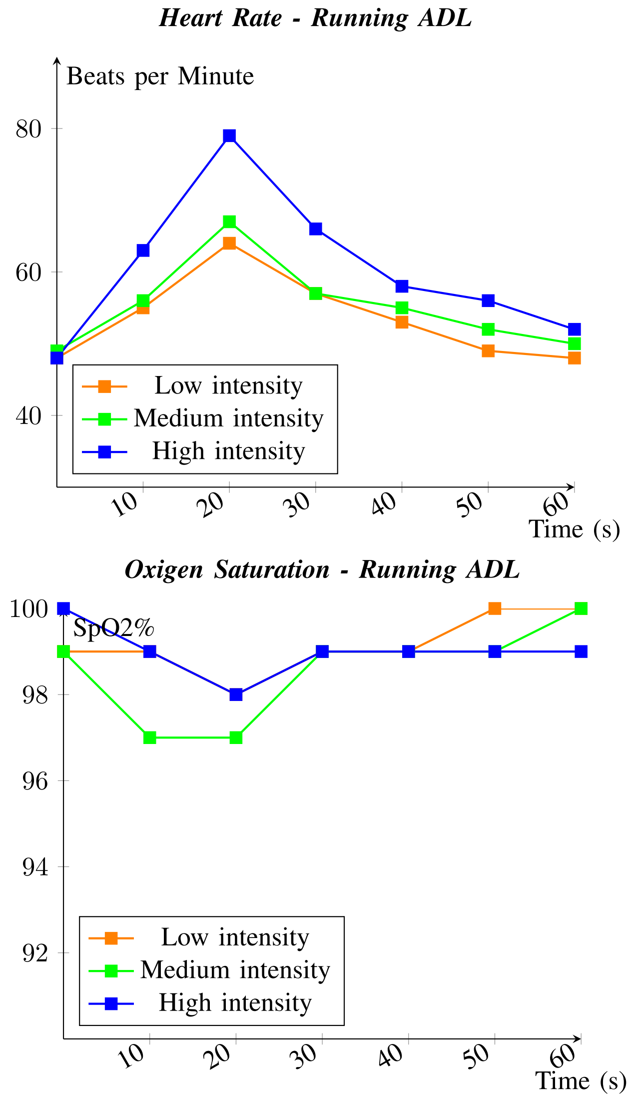

Fig. 6: Heart rate and oxygen saturation (SpO2) monitoring - Running activity

is more prepared to detect false positives, than to avoid false negatives, so there is no need to increase the value of a_{th}.

With the system's ability to detect possible falls and display cardiac and SpO2 values on the watch, the user and their caregivers can have better control over the user's health, leading to a higher quality of life.

Conclusion

This work focuses on a distributed system that could improve the quality of life of the older population by monitoring their mobility and physiological parameters. Appropriate firmware was developed to satisfy the system requirements including real-time monitoring of falls and cardiac data. Validation tests have been carried out, with various results associated with user mobility together with cardiac monitoring including high-intensity movements.

Despite the difficulties in perfecting the fall detection algorithm, the findings presented suggest that based on this system, it is possible to provide reliable remote health monitoring for elderly users, also considering its reduced costs.

It would be fruitful to pursue further research about monitoring the health of the elderly to validate that non-intrusive remote health monitoring systems based on IoT in an aging society, has practical value. Further research in areas like ballistocardiogram (BCG) monitoring (24h cardiac monitoring), diabetes (blood glucose monitoring), asthma, among others.

Acknowledgment

This work was supported by Fundação para a Ciência e a Tecnologia, I.P. (FCT) [ISTAR Projects: UIDB/04466/2020 and UIDP/04466/2020].

References

[1] . O.-O. Max Roser and H. Ritchie, "Life expectancy,"Our World in Data, 2013,https://ourworldindata.org/life-expectancy.

[2] A. Clegg, J. Young, S. Iliffe, M. O. Rikkert, and K. Rockwood, "Frailty in elderly people," The Lancet, vol. 381, pp. 752–762, 9868 2013, issn: 1474547X. doi: 10. 1016/S0140-6736(12)62167-9.

[3] F. M. Xavier, M. Ferraz, N. Marc, N. U. Escosteguy, and E. H. Moriguchi, "Elderly people s definition of quality of life," Brazilian Journal of Psychiatry, vol. 25, pp. 31–39, 2003.

[4] R. Doshi, N. Apthorpe, and N. Feamster, "Machine learning ddos detection for consumer internet of things devices," in 2018 IEEE Security and Privacy Workshops (SPW), 2018, pp. 29–35. doi: 10.1109/SPW.2018.00013.

[5] D. Bandyopadhyay and J. Sen, "Internet of things: Applications and challenges in technology and standardization," Wireless Personal Communications, vol. 58, pp. 49–69, 1 May 2011, issn: 09296212. doi: 10.1007/S11277-011-0288-5.

[6] D. Moher, A. Liberati, J. Tetzlaff, et al., "Preferred reporting items for systematic reviews and meta-analyses: The prisma statement," PLoS Medicine, vol. 6, no. 7, 2009, cited By 34924. doi: 10.1371/journal.pmed.1000097. [Online]. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-68049122102&doi=10. 1371%2fjournal.pmed.1000097&partnerID=40&md5=ae3854790b86846c4e4519473a3a3417. vol. 10, pp. 57–76, 1 Jan. 2019, issn: 18685145. doi: 10.1007/S12652-017-0598-X.

[7] T. Shany, S. Redmond, M. Narayanan, and N. Lovell, "Sensors-based wearable systems for monitoring of human movement and falls," IEEE Sensors Journal, vol. 12, no. 3, pp. 658–670, 2012, cited By 197. doi: 10.1109/JSEN.2011.2146246. [Online]. Available: https : / / www . scopus . com / inward / record . uri ? eid = 2 - s2 . 0 - 84856846340 & doi = 10 . 1109 % 2fJSEN . 2011 . 2146246 & partnerID = 40 & md5 = 5477ee5e67102e71b40bc608bd03bfdf.

[8] F. Wu, H. Zhao, Y. Zhao, and H. Zhong, "Development of a wearable-sensor-based fall detection system," International Journal of Telemedicine and Applications, vol. 2015, 2015, cited By 134. doi: 10 . 1155 / 2015 / 576364. [Online]. Available: https://www.scopus.com/inward/record.uri?eid=2-s2.0-84924370518&doi=10. 1155%2f2015%2f576364&partnerID=40&md5=9f3cbbe7c346b8f9c9a8edc23909b661

[9] Hasa, Difference between hypothesis and research question: Meaning, features, characteristics, usage, Aug. 2016. [Online]. Available: https : / / pediaa . com / difference-between-hypothesis-and-research-question/.

[10] J. v. Brocke, A. Hevner, and A. Maedche, "Introduction to design science research," in Sep. 2020, pp. 1–13, isbn: 978-3-030-46780-7. doi: 10.1007/978-3- 030-46781-4_1.

[11] K. Peffers, T. Tuunanen, M. A. Rothenberger, and S. Chatterjee, "A design science research methodology for information systems research," Journal of Management Information Systems, vol. 24, no. 3, pp. 45–77, 2007. doi: 10 . 2753 / MIS0742 - 23 1222240302. eprint: https://doi.org/10.2753/MIS0742-1222240302. [Online]. Available: https://doi.org/10.2753/MIS0742-1222240302.