Towards an IoHT Platform to Monitor QoL Indicators

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Abstract: The Quality of Life has been studied for a long time, and the World Health Organization defines it as the individual perception about life regarding four major domains: physical, psychological, social, and environmental. The relevance to study QoL lies in the search for strategies able to measure a patient's well-being. Without these strategies, treatments, and technological solutions that aim to improve people's QoL would be restricted to physicians' implicit and subjective perceptions. Thus, there are many instruments for formal QoL assessment (usually questionnaires). However, the use of these instruments is time-consuming, non-transparent, and error-prone. Considering this problem, in this work, we discuss the proposal to use the Internet of Health Things (IoHT) to collect data from smart environments and apply machine learning techniques to infer QoL measures. To achieve this goal, we designed an IoHT platform inspired by the MAPE-K loop. Our literature review has shown that this idea is promising and that there are many open challenges to be addressed.

1 INTRODUCTION

Over the past few years, the use of technologies in healthcare and medical care has grown (Oliveira et al., 2021b). For example, years ago, it was practically unfeasible to continuously monitor a patient without the intrusive need of a robust hospital infrastructure (Islam et al., 2015). However, advances in the Internet of Things (IoT) such as sensors miniaturization, efficient communication protocols, expansion in data processing capacity, application of intelligent algorithms, and even more secure approaches to guarantee the privacy of patients have made possible a revolution in the healthcare area (Meskó, 2014).

In this way, the Internet of Health Things (IoHT) emerges from the application of IoT in healthcare (Rodrigues et al., 2018) and it is possible to cite many examples of IoHT solutions. For example, there are non-invasive glucose sensing (Istepanian et al., 2011), electrocardiogram monitoring (Agu et al., 2013), elderly fall detection (Almeida et al., 2016), and many others.

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In general, these solutions have been proposed to achieve i) individual benefits, by increasing safety and well-being; ii) economic benefits, by improving the cost-effectiveness of limited healthcare resources; and, finally, iii) social benefits by promoting better living conditions (Dohr et al., 2010).

Regarding the cost-effectiveness of healthcare systems, world society has experienced a phenomenon that has put much pressure on them: population aging (Nations, 2019). The United Nations (UN) projected that, in 2050, there will be 1.5 billion of older persons. The population aging process is highly positive since it indicates that we are progressing as a society. However, this new scenario brings new challenges. Among them, we can highlight the need for a healthcare system focused on preventive care (Gmeinder et al., 2017). Today, it is common to act only when the patient becomes ill (Marvasti and Stafford, 2012).

The Organization for Economic Co-operation and Development (OECD) pointed out that only 2.8% of health spending goes on prevention, and only 7% of this part was focused on early disease detection (Figure 1) (Gmeinder et al., 2017). Furthermore, the last World Health Organization (WHO) report indicates that this percentage grew only to 5% in 2020 (Vrijburg and Hernández-Peña, 2020).

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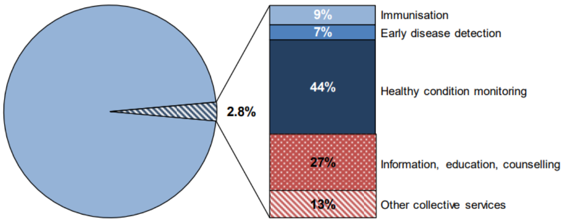

Figure 1: Fraction of health expenditure applied in preventive health strategies (Gmeinder et al., 2017).

Thus, one of the strategies that can improve the effectiveness of healthcare systems is the continuous monitoring of people's Quality of Life (QoL) in order to anticipate the development of health issues related to physical, psychological, social, and environmental aspects. According to the WHO, it is crucial to measure the QoL because it has a close relationship with the health status, and it provides valuable data to medical practice (Estrada-Galinanes and Wac, 2018).

Nevertheless, given the available techniques and tools, it is possible to state that seamless Quality of Life (QoL) monitoring is complex, expensive, non-transparent, and error-prone. It is complex because there are at least 150 strategies to measure QoL (Gill and Feinstein, 1994), and it remains difficult to firmly define QoL (Karimi and Brazier, 2016). It is expensive and non-transparent because these strategies (usually questionnaires) should be self-rated by the patient or should be applied by a healthcare professional (Bowling, 2005). Furthermore, it is error-prone since an active answer to a questionnaire can add a bias in the outcomes (Crane et al., 2016).

Thus, this work presents ongoing research that aims to create an IoHT platform able to support the development of self-adaptive applications (Vansyckel et al., 2013) focused on monitoring and improving users' Quality of Life. This study is part of a larger STIC-AmSud[1] project - called Angel - which aims to provide a robust Internet of Things (IoT) platform to Ambient Assisted Living, offering support to the improvement of Quality of Life (QoL), especially for persons with chronic diseases, older adults and persons with acute diseases under medical monitoring. The idea is to use the Internet of Things (IoT) to obtain and enrich environmental data in order to infer QoL levels, monitor health vital signs, and identify atypical situations such as falls and nocturia.

In this paper, we discussed the advances in our data collection module. The following sections discuss our background, proposal, ongoing proof of concept, and final remarks.

[1] STIC-AmSud: sticmathamsud.org/stic/proyectos.

2 BACKGROUND

Before any formal definition, having a better Quality of Life is probably the greatest desire of humankind. Naturally, this desire has driven the development of studies focused on improving people's QoL (Baker et al., 2017), mainly because there is a close relationship between health and QoL (Guyatt et al., 1993).

However, despite being discussed for a long time (Elkinton, 1966), the term Quality of Life is confusing and can be observed from many perspectives (Karimi and Brazier, 2016). The QoL can be related to the absence of chronic diseases, perception of loneliness, physical well-being, and understanding of the aging/death process. In this work, the WHO definition for Quality of Life was considered the main reference. For WHO, QoL can be described as the individual perception of life in a sociocultural context and concerning goals, expectations, and personal standards (WHOQoL Group, 1994).

From this definition, many mechanisms to evaluate QoL have been proposed. One of the most cited is the WHOQOL-BREF questionnaire (Skevington et al., 2004) due to its reliability and cross-cultural validity. The WHOQOL-BREF was evaluated in 23 countries (including Brazil), and it is available in 19 different languages. It has twenty-six (26) questions distributed into four domains: physical, psychological, social, and environment.

The "Physical" domain assesses motor facets such as daily living activities, medicines' dependence, mobility, sleep quality, and work capacity. The "Psychological" domain is related to the bodily image, negative and positive feelings, self-esteem, spirituality, and other mental health aspects. The "Social" domain observes personal relationships, social support, and sexual activity. Finally, the "Environment" domain aims to evaluate the environmental facets such as freedom, safety, security, participation in leisure activities, pollution, noise, traffic, and climate.

Unfortunately, the continuous application of this kind of instrument is tedious and bothersome (Sanchez et al., 2015), which makes it challenging to engage the participants. Therefore, the QoL continuous monitoring is still an open problem due to the complexity of the measurement instruments and the invasive approaches that do not preserve privacy (Oliveira et al., 2021b). The relevance of this problem emerges from the health benefits that can be achieved from up-to-date and accurate QoL information (*e.g.*, early interventions). Due to this, some studies have been conducted to find strategies to use the Internet of Things for seamless QoL monitoring.

3 RELATED WORK

In order to compose our related work, a literature review was performed on papers indexed on Elsevier's Scopus database. Our search string was composed of the following terms and their synonyms: "*smart quality of life, passive sensing, internet of health things, platform and machine learning*". The first two terms were included to ensure the retrieval of three control papers (previously identified by the authors). The other terms are directly associated with our final goal: to build a platform to support the development of IoHT systems that use Machine Learning to monitor and improve users' QoL.

The Scopus database was selected based on its coverage[2] of software engineering venues and relevant digital libraries such as ACM, IEEExplorer, Science Direct, and Springer. Thus, the selected papers represent a suitable sample to describe this study area. Furthermore, it is also important to note that we did not include any date restriction.

Initially, 122 papers were recovered, but only 13 were chosen after full reading. The eligibility criteria were: be a primary study, written in English, fully available on the Web, and with more than 5 pages; be published in conferences or journals; and discuss IoHT solutions to monitor QoL automatically.

Table 1 summarizes the 13 selected papers and our work. However, before starting the discussion of these works, we would like to highlight the difficulty in building a search string capable of differentiating studies focused on strategies to automate QoL measurements or that seek to correlate data collected by IoHT systems with measurements made by QoL questionnaires; from the studies that bring a specific proposal for a health problem. In general, both kinds of these studies use the terms Quality of Life, monitoring, and improvement. Thus, we argue that the term "Smart Quality of Life" is a suitable candidate to represent this research area. Within this context, the first authors[3] to use this expression were (Qiu et al., 2020). Unfortunately, the authors did not provide a formal definition for this term. Therefore, we present here a formal definition inspired by the WHO statement.

Smart QoL can be described as the perception of a person's Quality of Life from individual and contextual data acquired in Smart Environments using ubiquitous technologies. Usually, this perception is built through intelligent algorithms, and, over time, it can be used to detect health issues. Now, in light of this definition, it is possible to discuss our related work.

[2]Scopus Coverage: elsevier.com/?a=69451.

[3]Other authors have used this term, but in the context of smart cities.

We decided to group on the top of Table 1 case studies. Thus, the criteria "Deal with heterogeneity?", "Use any semantic model?", "Provide AI for data analysis?", and "Allow strategies to adapt user's environment" were filled with a dash because they are not applicable for them.

The studies presented by (Bade et al., 2018), (Kim et al., 2019), (Lee et al., 2019), (Angthong and Veljkovic, 2019), (Oliveira et al., 2021a), and (Brudy et al., 2021) were classified as longitudinal studies because they involve analyzing the participants data through an extended period in order to prove the correlation between health data and the patients' QoL. Although these studies do not present software artifacts as the main contribution, their discussion is relevant to indicate strategies for evaluating solutions that use health data to infer the quality of life of their users. All these works (excluding only the study conducted by (Lee et al., 2019)) used commercial smart bands and their native applications. This decision is probably related to the costs of these devices (values between \$15 and \$60 dollars). In general, devices with higher processing power that allow the development of native apps for their platforms are expensive (values above \$300 dollars). Another difficulty observed in these studies is the absence of APIs for data extraction, which makes this extraction an arduous process.

Regarding the data analysis, all of these longitudinal studies present statistical analyzes to validate their hypotheses. (Bade et al., 2018) and (Oliveira et al., 2021a) proved that there is a correlation between physical activity data and the QoL of people with cancer. Similarly, (Kim et al., 2019) shown this correlation for hospitalized patients with spinal issues; (Lee et al., 2019) for patients with fibromyalgia; (Angthong and Veljkovic, 2019) for adults with foot-ankle condition, and (Brudy et al., 2021) for children with congenital heart disease. The results of these studies can be generalized to state that **it is possible to use data collected by smart objects to measure the Quality of Life of patients even with different QoL questionnaires and for different health conditions**. This opportunity has also been reinforced in renowned medical journals (Huckvale et al., 2019). Unfortunately, none of these studies made their datasets available, which hinders the advancement in this study area. Currently, there are many data silos without a semantic representation that allows its use in further investigations.

To conclude this first group of works, (Concheiro-Moscoso et al., 2021) brings a protocol to assess the impact of stress in workers' QoL. Their main contribution is to present a guide on conducting studies that seek to correlate health data with QoL facets.

Table 1: Papers selected in the literature review compared with our proposal.

Work	Contribution	Deal with hetero-geneity?	Use any semantic model?	Provide AI for data analysis?	Allow strategies to adapt user's environ-ment?	Domains	Profile	# of Part.	Env.	Devices	Analysis
(Bade et al., 2018)	Longitudinal study	-	-	-	-	Physical	Patients with Lung Cancer	30	Not specified	Fitbit Zip and Smartphone	Spearman rank correlation
(Kim et al., 2019)	Longitudinal study	-	-	-	-	Physical	People with spinal issues	22	Hospital	Fitbit Charge	Pearson correlation and regression analysis
(Lee et al., 2019)	Longitudinal study	-	-	-	-	Physical	Fibromyalgia patients	14	Not specified	Specific wearable built for this study	Statistical analysis
(Angthong and Veljkovic, 2019)	Longitudinal study	-	-	-	-	All	Adults with foot- and ankle-related conditions	52	Not specified	Foot pod (Garmin)	Pearson's correlation
(Oliveira et al., 2021a)	Longitudinal study	-	-	-	-	All	Lymphoma patients	16	Not specified	Microsoft Band 2	Statistical analysis
(Concheiro-Moscoso et al., 2021)	Study Protocol	-	-	-	-	Physical	Adults	11	Work	Xiaomi Mi Band 3	Statistical analysis
(Brudy et al., 2021)	Longitudinal study	-	-	-	-	All	Children with congential heart disease	343	Not specified	Garmin vivofit Jr	Logistic regression
(Merilahti et al., 2012)	Model	No	No	Yes	No	Physical	Older adults	19	Not specified	Actigraphy, Bed sensor, Omron Walking Style II pedometer and Omron 705IT	Spearman correlation and k-means clustering
(Vargiu et al., 2014)	Methodology	Yes	No	Yes	No	All	People with disabilities	Not informed	Home	Brain/Neural Computer Interface (BNCI), inertial sensors, environmental sensors, smart home devices	C4.5 and k-NN
(Bono-Nuez et al., 2014)	System	No	No	Yes	No	Physical	Older adults	Not informed	Smart Kitchen	Kitchen appliances, Zigbee sensors, RFID and portable devices	Self-organizing maps (SOM)
(De Masi et al., 2016)	Platform	No	No	Yes	No	All	Generic	Not informed	Indoor and outdoor	Smartphone and Wearables	User data timeline
(Dobre et al., 2019)	Architecture	Yes	No	No	No	All	Older adults	Not informed	Indoor and outdoor	Smartwatch, smart shoes, camera	Statistical Analysis
(Rădulescu et al., 2019)	Framework	No	No	No	No	All	Older adults	17	Not specified	Not specified	Spearman correlation
Our work	Platform	Yes	Yes	Yes	Yes	Physical and Psy-chological	Adults	In progress	Indoor and Outdoor	Smartphones, Amazfit Bip, and Smart Home Devices	Machine Learning

The second group brings methods, frameworks, systems, and platforms as their main contribution.

In (Merilahti et al., 2012), the authors present a study about the performance of health monitoring technologies to estimate the physical function of older adults. They present a hypothesis that health data would predict pre-clinical measures. Thus, 19 older adults were analyzed through 84 days using wrist-worn activity monitors, bed sensors, pedometers, weight scales, and blood pressure monitors. The acquired raw data were transformed into 16 features, and they were analyzed using statistical correlation and clustering methods. Unfortunately, the results were not promising, indicating only a correction with the daily steps. However, this work brings interesting insights about which features can be used in this type of investigation and points out issues in data collection. Compared to our proposal, this paper presents only a specific model for the physical domain, which does not consider self-assessment questionnaires and does not concern itself with other aspects of IoHT (such as heterogeneity, semantic model, and environmental adaptation).

(Vargiu et al., 2014) propose a context-aware methodology to telemonitor QoL concerning the physical and social autonomy of people with disabilities. Thus, they adapted the EQ-5D-5L questionnaire to assess mood, health status, mobility, self-care, usual activities, and pain/discomfort. On the other hand, health data were collected by Brain/Neural Computer Interface (BNCI), inertial and environmental sensors, and smart home devices. Finally, the authors achieved good results using the C4.5 and k-NN algorithms. Nonetheless, due to the lack of real data, synthetic data was used.

(Bono-Nuez et al., 2014) focused their contribution in creating a QoL evaluation system to support the work of caregivers. The idea is to provide QoL assessments of older adults periodically to help decision-making of caring actions. Unlike other studies, the authors did not choose a QoL questionnaire as a reference. Instead, they decided to cluster the data using self-organizing maps (SOM). Nevertheless, their proposal was focused on smart kitchens, and it requires the analysis of a domain expert to interpret the results obtained by the SOM.

The work proposed by (De Masi et al., 2016) is probably the most related to our proposal. The significant difference is that the authors proposed a platform to support interdisciplinary studies related to Quality of Life. In contrast, we are focused on helping the development of IoHT systems capable of using data from Smart Environments to provide a closed adaptation loop. The authors present the first version of the mQoL Living Lab and the requirements for the second version in their paper. Unfortunately, this platform is not publicly available, and it was not possible to conduct a more in-depth test.

(Dobre et al., 2019) propose an IoT architecture to deliver non-intrusive monitoring and support older adults' healthcare. One of the most interesting points of this work lies in the authors' concern about inherent Internet of Things challenges, such as interoperability. The architecture was designed with a modular structure and, similar to the work proposed by (De Masi et al., 2016), the data analysis module is aimed at conducting scientific studies. However, this work did not address semantic models for QoL data, intelligent techniques to infer QoL, and strategies to act in the environment.

The work proposed by (Rădulescu et al., 2019) brings a framework to find a correlation of health parameters with QoL questionnaires. The authors deal with this problem using mathematical models. They selected the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS), which uses the concept of "ideal" and "anti-ideal" solutions and computes the Euclidean distance to find an overall health index for the elderly. Nonetheless, the method was evaluated only with synthetic data, and its complexity makes its adoption in several contexts difficult.

Finally, the analysis of these papers highlights that there are still opportunities in developing platforms that enable the collection of health data, the processing of these data using intelligent algorithms, the planning of interventions in case of risky situations, and the environment adaptation. In other words, a closed loop of health care that seeks to identify health issues before they become a reality.

4 OUR PROPOSAL

This investigation has the final goal to develop an IoHT solution to collect data from smart environments and apply machine learning to infer QoL measures. Moreover, this solution should allow high-level health interventions to adapt the user's environment.

To achieve this goal, we are proposing a platform to support the development of this kind of system. The rationale for building a platform lies in the benefits obtained by software reuse since other researchers or practitioners can use it to implement solutions for specific contexts (Araújo et al., 2018). In addition, the platform is being designed to address challenges such as lack of interoperability, high volatility, high development cost when it involves AI, absence of a semantic model for QoL data, and difficulties to bring healthcare professionals closer to the development process (Oliveira et al., 2021b).

Figure 2 presents an overview of this proposal. We decided to organize the platform modules following the MAPE-K loop framework (IBM, 2005). Hence, the platform will support collecting and analyzing data, plan what actions should be taken based on the analysis result, and adjust the environment. Further-

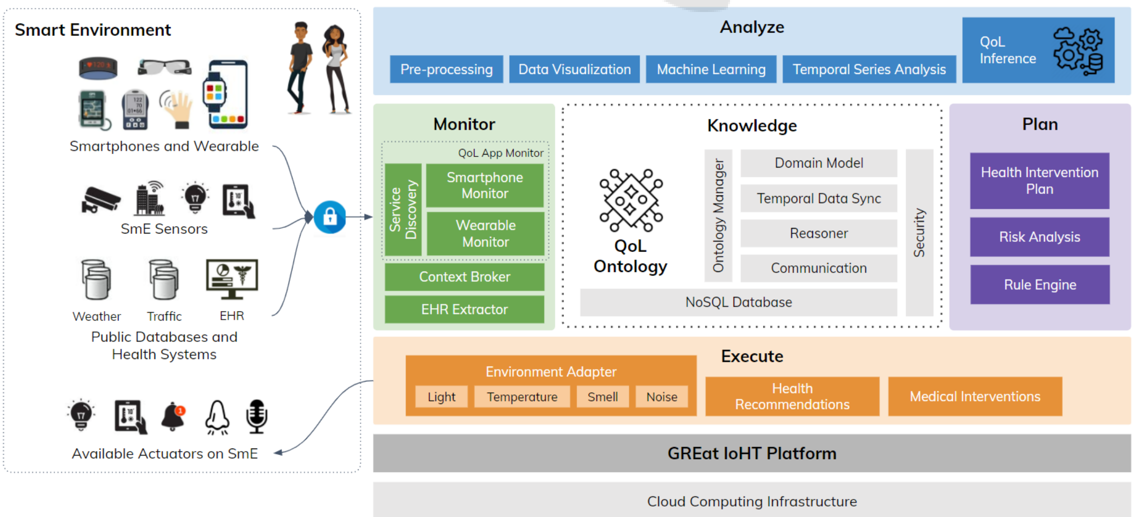

Figure 2: IoHT platform design inspired on the MAPE-K loop.

more, it will be possible to represent the knowledge using a QoL ontology.

In the monitor are the modules responsible for obtaining user data. These data can be collected from mobile devices (*e.g.*, smartphones), context brokers, or EHR (Electronic Health Record) systems. As discussed in our related work, the literature already has evidence that data collected from wearables can infer QoL aspects. In this way, this proposal argues that an expanded view of devices present in smart environments allows a broad and accurate QoL inference.

Additionally, it will be integrated a previous work called LoCCAM-IoT (Andrade et al., 2020), which is a multifaceted infrastructure to support the development of self-adaptive IoT systems. This infrastructure has three major modules: i) CoAP-CTX, an extension of the CoAP protocol for context-awareness device discovery; ii) LoCCAM, a middleware for acquisition and context management that uses smartphones as a decision center; and iii) SUCCEEd, which was created to support the self-adaptation using workflows.

In the analysis area, the platform will provide machine learning techniques adapting the Athena tool, which is a visual, customizable, cloud-based tool to support the development of systems that require Computational Intelligence (CI) techniques. It uses the abstraction of visual modules to encapsulate the CI algorithms allowing their interconnection to solve complex problems (Oliveira et al., 2018). All these techniques should support the creation of an intelligent model to infer QoL.

Monitoring and data analysis will provide a QoL profile for the user. With this profile, it will be possible to identify risk situations and plan health interventions. These interventions - defined by health professionals - can be recommendations for changes in habits; or even the execution of adaptations in the environment. In critical cases, it will be possible to request medical interventions.

Finally, the execution of this loop generates a vast amount of data, which represents the knowledge acquired in that context. Thus, the platform also provides an ontology for representing and storing data.

5 PROOF-OF-CONCEPT

A Proof-of-Concept (PoC) is in progress in order to validate our proposal. This PoC aims to anticipate the best strategies for collecting data from users and which machine learning algorithms are suitable for the inference process.

For this, we developed an Android application – called QoL Monitor – to collect contextual and health data from users. In this version, we collect sociodemographic and anthropometric data, sleep duration, daily steps, calories spent, physical activities, heart rate, location, apps usage time, and the number of calls made or received. To do that, it was necessary to integrate our app with the Google Fit API. Thus, users who participate in this study can use different wearables as long as they are integrated with the Google Fit account.

Since we are looking to validate the creation of intelligent models to infer users' QoL, it will be necessary for them to answer questionnaires informing their QoL perception periodically. We are working to reduce the use of these questionnaires. However, today, they are our best alternative to calibrate our machine learning models, as they have been validated with many participants in different countries.

Figure 3 presents the QoL Monitor data collection workflow. It is possible to observe some impor-

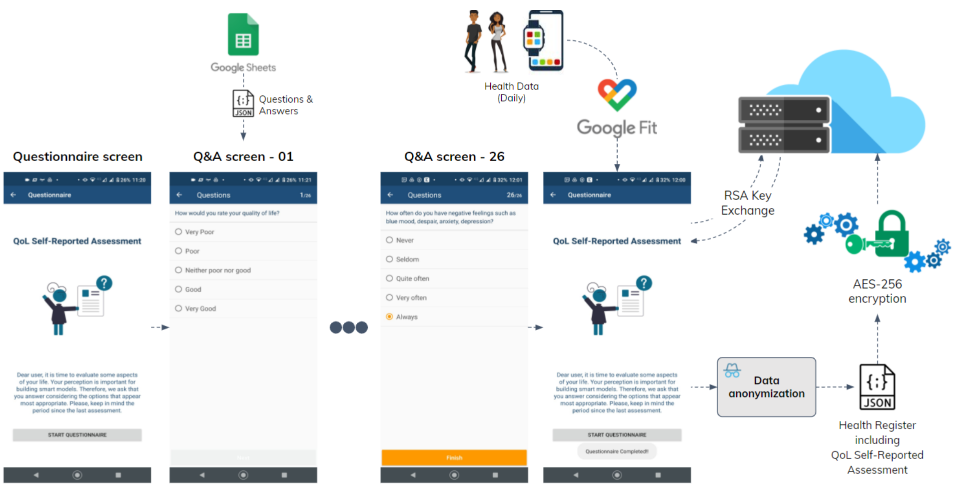

Figure 3: QoL Monitor data collection workflow.

tant points: i) the questionnaire can be externally customized, making easier changes throughout the study or even the validation of another questionnaire; ii) historical health data is obtained via Google Fit API; and iii) before sending the data to the server, they are anonymized and encrypted using AES-256 algorithm, in addition to the exchange of RSA keys for secure communication with the server.

Currently, the QoL Monitor has been finished and internally validated by the researchers. Thus, our next step is to request permission for the ethics committee to start a pilot study with a larger number of participants. Our purpose is also to create a public and anonymous database to improve QoL inference models. Unfortunately, to the best of our knowledge, no databases were found able to correlate contextual and health data with self-report QoL questionnaires.

6 FINAL REMARKS

This work is just beginning, and there are many points to be defined. However, we argue that this paper discusses an interesting research topic to guide the scientific community towards an IoHT platform to monitor and improve people's Quality of Life.

In this paper, we present the platform's design inspired by the MAPE-K loop. Using this approach, it is possible to support IoHT applications able to monitor and analyze user data and plan and execute interventions in the environment.

Furthermore, we state that there is a growing need for investments in solutions capable of anticipating health issues. This kind of solution has the potential to move our healthcare system from passive care to active care, increasing its cost-benefit. Due to this, we also discussed 13 related works and proposed a definition for the term Smart Quality of Life.

As our future work, we highlight the conclusion of our PoC; the investigation of which health issues can be early detected by analyzing QoL over time; the development of the first version of our IoHT platform; and the conduction studies to validate the platform.

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