Analytical Model and Reference Architecture for QoL-based Systems

Pedro A. M. Oliveira[1,2], Rossana M. C. Andrade[2], Pedro A. Santos Neto[3], Wilson Castro[2], Evilasio Costa Junior[2], Ismayle S. Santos[4] and Victória T. Oliveira[2,*]

[1]Federal Institute of Education, Science and Technology of Maranhão, Pedreiras, Brazil
[2]Federal University of Ceará, Fortaleza, Brazil
[3]Federal University of Piauí, Teresina, Brazil
[4]Ceará State University, Fortaleza, Brazil

Abstract

Software Engineering (SE) is critical for developing robust and efficient software systems, particularly on the Internet of Health Things (IoHT), which leverages interconnected devices for health management. IoHT enables continuous monitoring and real-time data collection, significantly enhancing patient care and Quality of Life (QoL). Despite existing research, there is a gap in artifacts explicitly designed for QoL-based IoHT systems. This paper proposes a reference software architecture and an analytical model for QoL-based Systems. The architecture is inspired by the MAPE-K (Monitor, Analyze, Plan, Execute - Knowledge) loop framework and follows a layered approach encompassing the Business, Application, Middleware, Network, and Perception layers. It integrates multiple data sources, processes information intelligently, and executes adaptive interventions in the user's environment to improve QoL. The architecture is divided into four key stages: Monitoring, where data is collected from various Internet of Things (IoT) devices; Analysis, where data is processed and interpreted; Planning, which involves creating intervention plans based on the analyzed data; and Execution, where the planned interventions are carried out. The analytical model generates health interventions aimed at increasing the user's lifespan by measuring quality of life through data-based instruments, which infer personal health indicators by analyzing contextual data produced by IoT devices. The proposed artifacts enhance system reliability and patient outcomes in smart healthcare environments.

Keywords

Software Engineering, Analytical Model, Software Architecture, Quality of Life, Internet of Health Things

1. Introduction

The Internet of Things (IoT) refers to the interconnection of physical devices via the Internet to achieve common goals, thus enabling physical devices to act and sense transparently [1]. These features allow the IoT to be used in various domains [2], among which it is worth mentioning health, where IoT is increasingly present in medical devices, software applications, and health services [3].

Furthermore, IoT can be called the Internet of Health Things (IoHT) when applied to health. IoHT technologies enable continuous monitoring, real-time data collection, and the implementation of immediate interventions, which is vital for effective health management [4]. Consequently, these technologies provide a better patient experience with cost reduction due to decreased human intervention [5].

In addition, another significant benefit of IoHT is improving Quality of Life (QoL) through, for example, patient monitoring, allowing them to monitor themselves and thus ensure self-management of health conditions [6]. Moreover, it is worth noting that the World Health Organization (WHO) defines QoL as an individual's perception of their life within a sociocultural context concerning their goals,

ICAIW 2024: Workshops at the 7th International Conference on Applied Informatics 2024, October 24–26, 2024, Viña del Mar, Chile
*Corresponding author.
pedro.oliveira@ifma.edu.br (P. A. M. Oliveira); rossana@ufc.br (R. M. C. Andrade); pasn@ufpi.edu.br (P. A. Santos Neto); wilson.castro@great.ufc.br (W. Castro); evilasio@great.ufc.br (E. Costa Junior); ismayle.santos@uece.br (I. S. Santos); victoria.oliveira@great.ufc.br (V. T. Oliveira)
0000-0002-3067-3076 (P. A. M. Oliveira); 0000-0002-0186-2994 (R. M. C. Andrade); 0000-0002-1554-8445 (P. A. Santos Neto); 0000-0002-0281-2964 (E. Costa Junior); 0000-0001-5580-643X (I. S. Santos)

expectations, and personal standards [7]. Besides that, according to the WHO, it is important to assess QoL because it has a close relationship with the health status [8, 9].

Also, it is crucial to mention that the general elements of IoHT systems include many kinds of sensors for collecting patient data. There are also applications developed for user terminals, such as smartphones, smartwatches, or specific embedded devices, which process this data. These terminals connect to gateways, which transmit the data over the Internet using short-range communication protocols such as Bluetooth Low Energy (BLE). Gateways usually act as a hub between a sensor layer and cloud services or clinical servers that store process, and analyze the data. In this way, patient data stored in Electronic Health Record (EHR) systems can be easily accessed [5].

Therefore, IoHT systems must meet strict requirements for low latency and high reliability, as failures can directly impact users' health, and the data are highly sensitive [10]. Furthermore, IoT devices are often embedded and highly heterogeneous, requiring software that adapts to the different system characteristics and ensures high availability and resilience [11].

In this context, Software Engineering (SE) plays an essential role in effectively integrating and managing these devices, ensuring that IoT systems operate reliably and efficiently. Given that SE applies systematic, disciplined, and measurable approaches to software development, operation, and maintenance, it provides a solid foundation for creating robust and efficient applications [12].

Additionally, as [13] points out, SE can be understood as a layered technology in which the process forms the foundation, methods provide technical guidelines, and tools offer automated or semi-automated support. This discipline is fundamental for ensuring software systems' quality, reliability, and efficiency in various contexts.

However, despite numerous studies on the use of SE in the context of IoT systems, software artifacts are still required to keep up with the growing demand for monitoring and QoL-based solutions [6, 14, 15].

In light of this context, this study proposes a reference software architecture and an analytical model for QoL-based Systems. The MAPE-K reference model inspires the proposed architecture [16] to implement adaptation loops for Self-Adaptive Systems (SAS) [17]; however, its focus is not on creating SAS but on the adaptation caused in the user's environment to improve their QoL. The analytical model uses data from sensors and wearables to infer health indicators and provide personalized health recommendations through machine learning techniques.

This paper is organized as follows: in Section 2 and Section 3 core concepts related to this study and related work are discussed; in Section 4, our QoL-based Systems Analytical Model is presented; in Section 5, our proposed Software Architecture is presented; in Section 6, a use case scenario is provided; and in Section 7, we conclude this paper with final remarks.

2. Background

The IoT has brought significant innovations to various domains, especially healthcare, through the IoHT. The IoHT is a subset of the IoT that allows medical devices and medical information systems to be connected, thus enabling the continuous, real-time collection of patient data. This connectivity expands the possibilities for immediate interventions, which can be adaptive responses to certain conditions in the patient's environment.

The general IoHT architecture used as the baseline for this paper was presented by [5] and depicted in Figure 1. As highlighted in [5], IoHT solutions incorporate a network architecture designed to connect patients to healthcare facilities. These solutions encompass E-Health systems in various uses, such as electrocardiography, heart rate monitoring, electroencephalography, and diabetes, among other vital signs, through biomedical sensors that collect user data.

In addition, due to the restrictions of these sensors, the data is processed by applications developed for a user terminal, such as computers, smartphones, and smartwatches. Moreover, a gateway connects the user terminal to a clinical server or cloud services for data processing and storage. The connection is made through short coverage communication protocols, such as BLE or 6LoWPAN (IPv6 over Low Power Wireless Personal Area Networks) following the IEEE 802.15.4 standard. Alternatively, patient data can be stored in a health information system using EHR. This way, when the patient visits a doctor, the clinical history can be accessed easily.

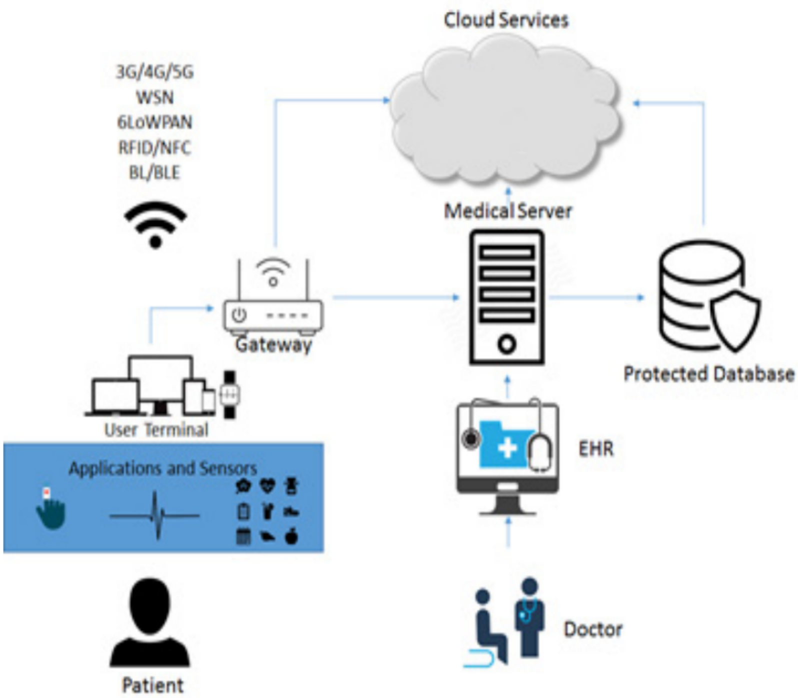

Figure 1: IoHT-based solution architecture [5]

Furthermore, it is worth mentioning the concept of SAS that is so important to this work. SAS are designed to automatically adjust their behavior in response to changes in their environment or internal conditions [17]. These systems are particularly valuable in complex and dynamic domains, such as the health sector, where the context can change rapidly. Using SAS in the healthcare sector, medical systems can respond dynamically to real-time data, improving patient care through timely interventions that adapt to the patient's current state of health and environmental factors.

In this context, the adaptability of SAS has great potential to be used effectively in QoL maintenance systems. This is because SAS can be used to continuously monitor patients and make autonomous decisions that affect treatment plans, and medication dosages, or alert medical professionals to potential problems before they become critical. For example, a SAS could adjust the monitoring parameters of a patient with a fluctuating condition, ensuring that the patient receives the appropriate level of care at all times, without requiring constant manual adjustments from healthcare professionals.

One of the most widely adopted frameworks for implementing SAS is the MAPE-K model [16], which stands for Monitor, Analyze, Plan, Execute, and Knowledge. The MAPE-K model, shown in Figure 2, structures the adaptation process into a control loop that continuously monitors the system or environment, analyzes the data to detect any deviations from expected behavior, plans a response to these deviations, and executes the necessary actions. The "Knowledge" component represents the data and policies that guide the system's behavior throughout this loop.

As mentioned in [18], MAPE-K can be applied in different scenarios. In addition, MAPE-K allows automatic adaptation, offering greater autonomy and less need for manual intervention, unlike other frameworks evaluated that rely on human intervention or less autonomous approaches.

In this way, its robust structure and ability to adapt to different scenarios is ideal for technology applied to health. In this domain, processes are generally based on data collection and analysis, followed by interventions traditionally carried out externally by the healthcare professional [5]. With the adaptation proposal, intervention within the loop can also be managed by the system, increasing the efficiency and autonomy of the process.

The architecture proposed in this paper uses the MAPE-K model, but the system is adapted not to itself but to the user's context, adjusting it to their needs.

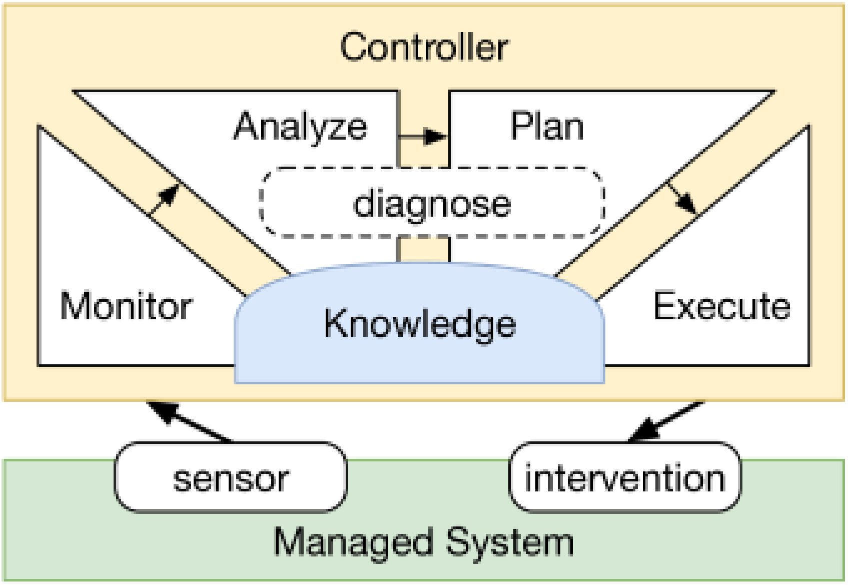

Figure 2: MAPE-K reference model for Self-Adaptive Systems [19]

Integrating MAPE-K with the IoHT Architecture can improve the adaptive management of connected health systems. Here's how:

- **Monitoring:** Sensors in an IoHT system provide continuous data on the state of patients and the healthcare system. MAPE-K uses this data to monitor and evaluate the condition of devices and the health of patients [20].
- **Analysis:** The analysis phase in MAPE-K can use machine learning and artificial intelligence algorithms to interpret large volumes of health data collected by IoHT devices, identifying patterns or anomalies that may indicate problems [21].
- **Planning:** Based on the analysis, the system can plan automated interventions or recommendations for healthcare professionals or patients, such as medication adjustments or appointment alerts [22].
- **Execution:** MAPE-K guides the execution of planned actions, which can include automatic adjustments to treatment or notifications to caregivers. This can be integrated with IoHT systems to carry out these actions effectively [23].
- **Knowledge:** The knowledge accumulated through the MAPE-K cycle can be used to continuously improve the IoHT system, optimizing health data management and enhancing adaptive responses [21].

3. Related Work

A literature review was conducted on articles indexed in the Elsevier Scopus database to compose the related work section. Scopus was chosen based on its relevance and extensive coverage of various digital libraries. During the search, a limited number of analytical models and software architectures specifically for Quality of Life (QoL) monitoring systems were found. Therefore, the review also included the most cited papers discussing system architectures and analytical models in eHealth monitoring systems.

The terms used in the review were concatenated with logical operators and are described as follows:

- **"IoT", "IOHT", "Internet of Health Things", "Internet of Things":** To include studies related to the Internet of Things and specifically the Internet of Things for Health.

- **“Quality of Life”, “QoL”, “Health Monitoring System”:** To capture studies on quality of life and health monitoring systems.
- **“Analytical Model”, “Software architecture”, “System Architecture”:** To identify studies that discuss analytical models and software or system architectures applied to these contexts.

Regarding the selected studies, one notable is [15], which presents a fog computing architecture to enhance the energy efficiency, mobility, scalability, and reliability in health monitoring systems. The proposed architecture introduces smart e-Health gateways that provide local data processing, storage, and analysis, reducing the reliance on cloud servers and improving system responsiveness and efficiency.

Another significant contribution is presented by [24]. This study integrates edge computing and Low Power Wide Area Network (LPWAN) technologies to address the limitations of traditional IoT architectures, such as poor performance in unstable network environments and limited transmission bandwidth unsuitable for high data rate applications. The proposed system architecture utilizes wearable sensors and edge Artificial Intelligence (AI) to detect falls with high accuracy and efficiency by offloading computational tasks to edge gateways, reducing data transmission needs, and improving overall system responsiveness.

The study of [10] develops a scalable and fault-tolerant IoT architecture designed to maximize operational uptime and maintain connectivity using 6LoWPAN. This architecture includes backup routing mechanisms between nodes and continuous monitoring to identify and correct failures, such as sink node hardware malfunctions and traffic bottlenecks. If a sensor node becomes inactive, the gateway checks the connection and sends alerts if necessary. The architecture also supports extending the number of medical sensor nodes at a single gateway, facilitating real-time remote monitoring of biomedical signals, and ensuring system reliability and continuity.

In [4], the authors propose a three-layered fog computing architecture designed to minimize latency and network usage in time-sensitive health monitoring applications. Introducing a Load Balancing Scheme (LBS) effectively distributes the computational load among fog nodes, reducing latency and improving network efficiency.

The research of [25] presents a software architecture that leverages fog computing to enhance real-time data transmission and reduce latency. The proposed architecture includes a dynamic load-balancing approach and an efficient scanning mechanism to optimize the selection of fog nodes for IoT devices.

Lastly, [26] explores an analytical model to optimize alert strategies in health information systems based on patient trust. The study uses a Partially Observable Markov Decision Process (POMDP) to design optimal alert strategies considering patient adherence and trust levels. The model describes the dynamic interaction between patients and the Health Information System (HIS), with states including asthma control and trust levels. Observations are based on inhaler usage and clinical diagnoses, while interventions involve system alerts. Similar to our entities, the study addresses health monitoring using IoT devices and patient adherence, although it places more emphasis on trust dynamics.

These related works collectively illustrate advances in fog computing, IoT, and health monitoring systems. They provide a comprehensive basis for developing efficient, scalable, and reliable architectures and analytical models that improve quality of life through continuous health monitoring. However, they differ from our work in that they focus on infrastructure and are not aimed directly at QoL monitoring. Furthermore, few studies focus on software modeling and architecture. Most are concerned with infrastructure and network issues, highlighting a gap that needs to be filled.

4. Analytical Model

A model is a construct capable of describing observable phenomena [27, 28], which can be used to understand complex real-world situations and provide a basis for effective problem-solving [29]. In this way, analytical models use logical reasoning to model entities of a system and specify their relationships [30].

The analytical model proposed in this work was inspired by a previous study that brings a structured description for mobile Health (mHealth) applications [31] and can be seen in Figure 3. The entities (highlighted in the text using the underline) are represented by rectangles and their relationships by labeled arrows.

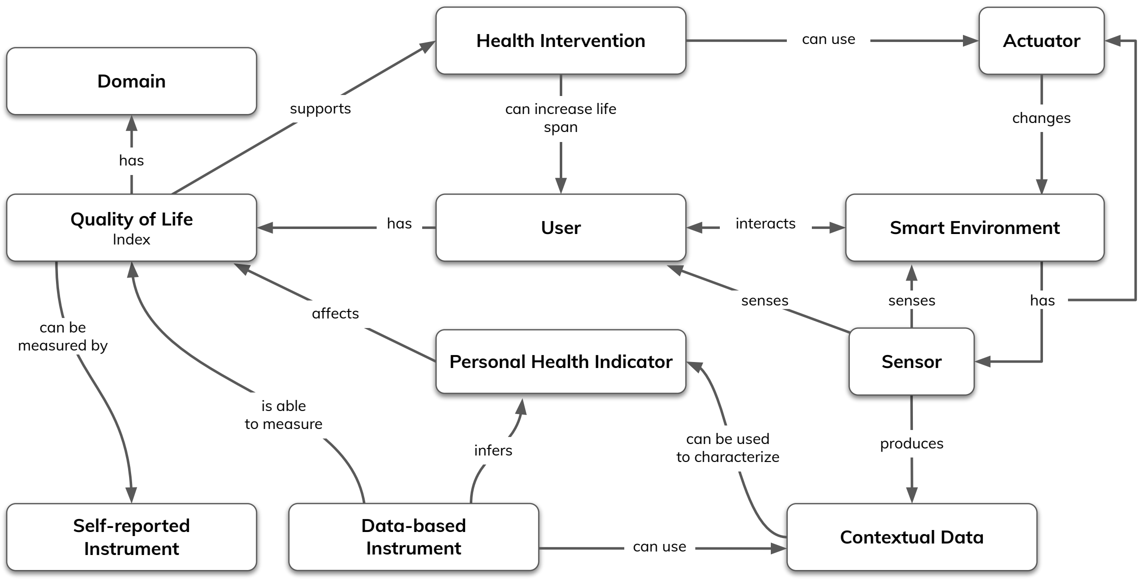

Figure 3: Proposed Analytical Model

At the center of this model is the User entity, which can interact with the Smart Environment. In this scenario, Smart Environments are characterized by Sensors and Actuators used to enhance users' lives [32]. A sensor produces Contextual Data from user and Environment sensing. With these data, it is possible to represent many Personal Health Indicators.

Every user has a Quality of Life index. QoL has several Domains, such as physical, psychological, social, and environmental [7]. The physical domain assesses motor facets such as daily living activities, medicine dependence, mobility, and sleep quality. The psychological domain relates to body image, negative and positive feelings, self-esteem, and other mental aspects. The social domain observes social relationships, and the environment domain aims to evaluate the environmental facets.

However, the usage scenarios presented in this work focus on physical and psychological domains. These two domains were selected due to their strong influence on the patients' Health and the availability of data to characterize each of them.

Based on the choice of domains, QoL scores can be measured using instruments such as Self-reported Instrument (*e.g.*, WHOQOL-BREF[1] [7]). This score is helpful for medical practice as it represents the patient's quality of life [33]. The proposed model also predicts the use of Data-based Instrument to infer users' QoL from contextual data as an alternative strategy.

These data-based instruments, for example, can leverage machine learning algorithms to learn and adapt from contextual data. This enables more dynamic and context-sensitive QoL assessments. Examples of such data-based instruments include the system presented in [14], which applies Self-Organizing Maps (SOM) to cluster data and detect health patterns, and the platforms QoL Smart Lab [34], which integrate data from smartphones and wearable devices with information from health questionnaires, allowing the collection and analysis of data for advanced QoL studies; and Healful [35],

[1]The WHOQOL-BREF was evaluated in 23 countries and is available in 19 different languages. It has 26 questions distributed into four domains: physical, psychological, social, and environmental

which combines IoHT data collection with machine learning algorithms and adaptation rules to infer users' quality of life.

Supported by the QoL scores, healthcare professionals can define Health Interventions such as adaptations to the user environment (when it is provided with smart actuators), periodic health recommendations (to promote changes in users' habits), or medical treatments (in critical cases). Such interventions can enhance user well-being and increase life span.

In addition, the proposed analytical model is flexible regarding personal health indicators, and its variety is essential for improving QoL predictions. This is evidenced by the study [36], which showed that the best fit of the structural equation model used to predict mental and physical health factors was achieved by integrating a wide range of subjective and objective indicators. This work considers five indicators in usage scenarios: daily mobility, physical activity level, sleep quality, loneliness level, and social mobility level.

The five health indicators – daily mobility, physical activity level, loneliness, social mobility, and sleep quality – were chosen based on the knowledge present in the literature that correlates each of them to physical and psychological Health (target usage scenarios for this work 6). For example, [37] presents an investigation correlating pedometer-based interventions with lower anxiety/depression and higher health-related QoL. Similarly, many other authors discuss the correlation between daily mobility and physical activity level with the patient's Quality of Life [38, 39, 40].

Regarding loneliness and social mobility levels, there is evidence that the social component strongly influences psychological health [41, 42]. [43] state that "*satisfying social relationships are essential for mental and physical well-being*". Therefore, these two indicators complement each other to observe the interaction of users and their daily commute.

The last indicator is sleep quality. Sleep is essential to restore the physical and psychological aspects of the human body [44, 45, 46]. According to [47], deep sleep restores muscles and removes waste from the brain, while the e Rapid Eye Movement (REM) re-energizes the mind.

Finally, it is essential to mention that the health indicators complement the QoL score and aid in understanding the results. Although helpful in medical practice, the score is not self-explanatory, thus requiring additional information for the patient to comprehend the results.

5. QoL-based Systems Architecture

Software architecture delineates the system's components and their interrelations [13]. Hence, an architecture should illustrate the system's structure and the collaboration of its components to fulfill the software's objectives. This section provides an overview of the architectural structure, addressing subsystems and modules, aligned with the analytical model described in section 4.

The proposed architecture is inspired by the MAPE-K (Monitor, Analyze, Plan, Execute - Knowledge) loop framework [16], which provides a robust and flexible model for QoL-based systems. This is due to its ability to integrate multiple data sources, process information intelligently, and adapt, allowing for smart interventions in the user's environment.

Furthermore, the proposed architecture consists of four main stages (see Figure 4), each responsible for a crucial monitoring and intervention cycle function.

Additionally, it is worth mentioning that MAPE-K loops generate a vast amount of data, representing the **knowledge** acquired in that context. These stored data enable continuous analysis and improvement of intervention models. Therefore, it is essential to mention that these data need to be stored in a way that can handle their high volume, scalability, and diversity.

Following, each stage is detailed, highlighting its responsibilities and the technologies that can be integrated.

5.1. Monitoring stage

The first state – **Monitor** – is responsible for collecting, aggregating, and filtering raw data from various sources in the environment. Data can be collected from various technologies, includ-

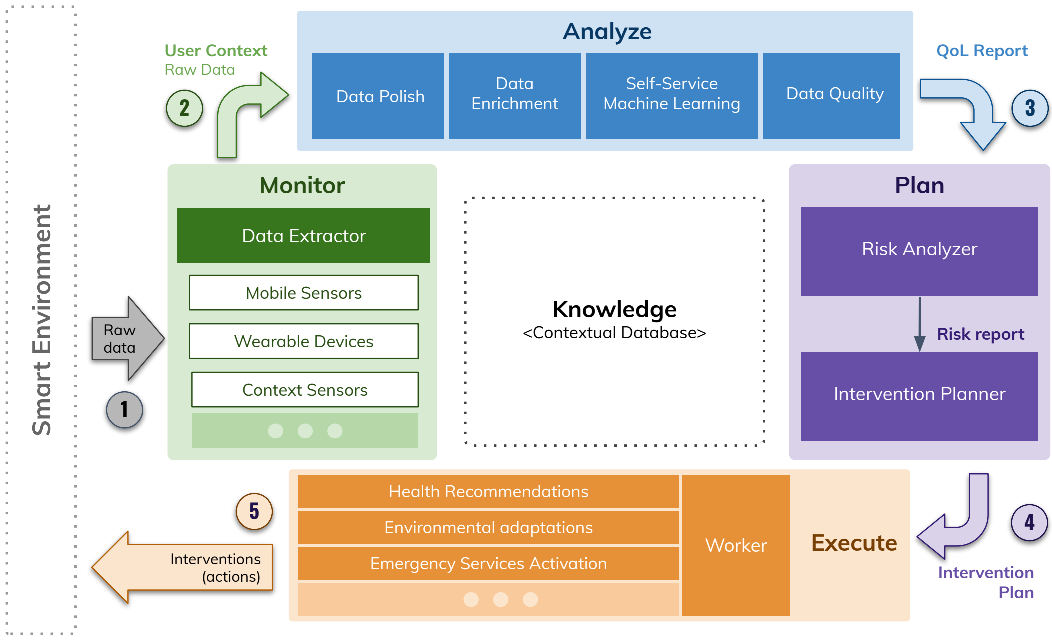

Figure 4: Proposed Analytical Model

ing Biometric Sensors capturing data such as heart rate, blood oxygen levels, blood pressure, and glucose; Activity Sensors including accelerometers, gyroscopes, pedometers, and sleep monitors; Context Sensors encompassing GPS, surveillance cameras, microphones, and proximity sensors to understand the user's environment; Environmental Sensors monitoring temperature, humidity, air quality, light, and noise; Wearable Devices such as smartwatches, fitness bands, smart clothing, and smart; and Mobile Devices smartphones and tablets running health applications to collect additional data. Given that, it is clear that different implementations of data extraction are required for each technology. Therefore, the Strategy behavioral pattern [48] was incorporated using a generic interface (referred to as Data Extractor). In this way, different implementations can be added easily for each new data source.

5.2. Analysis Stage

The **Analysis** state is responsible for processing and interpreting the data collected in the monitoring stage. This stage comprises four main modules, each performing a specific processing and data evaluation function. The first module is Data Polish: This module is responsible for refining and cleaning the raw data collected, which removes noise and inconsistencies, ensuring that the data is in a format suitable for analysis.

Next, Data Enrichment where the data is enriched with additional or derived information. This process can include combining different data sources, adding relevant context, or deriving new attributes from existing data. Self-Service Machine Learning follows this module, allowing the building of QoL indicators using machine learning algorithms. It enables users and professionals to create personalized models to predict and evaluate QoL.

At last, Data Quality ensures that the data used in the analysis is complete, correct, and accurate. It implements continuous checks and validations to maintain high data quality throughout the analysis process. The result of the analysis module is the QoL inference report. This report includes QoL scores for the domains worked on. With this QoL report, healthcare professionals can describe risk contexts that should be monitored.

In conclusion, the Pipe-and-Filter [49, 50] architectural pattern can be effectively utilized to implement these modules. This pattern allows for the sequential processing of data, where each module (filter) performs a specific transformation or analysis step and passes the data to the next module through a pipe. The pipeline structure facilitates the integration of additional modules or modifications without disrupting the overall flow, enhancing the system's adaptability to changing requirements. In this way, by adopting this approach, the system can achieve modularity, reusability, and flexibility, making it easier to maintain and extend.

5.3. Plan Stage

In the Planning stage, intervention plans are created based on the analysis reports. This stage involves two main modules: Risk Analyzer and Intervention Planner.

The risk analyzer consists of predictive risk analysis methods. It aims to predict factors that can affect QoL. This prediction can be carried out using methods that explore the simulation of scenarios based on specific factors and thus identify risks associated with certain contexts.

After the risk report, the intervention planner stage defines specific response actions using rules that evaluate contexts with associated risks and the appropriate interventions. These intervention actions compose the intervention plan that will be used in the next stage to address the risks encountered.

5.4. Execute Stage

The **Execute** stage performs the planned interventions (actions). These actions are executed by the Worker module, which uses specific modules for each action, such as the Health Recommendations module for sending notifications about the user's health; Environmental adaptations module adjusting the user's physical environment, such as lighting and temperature control, when actuators are available; and Emergency Services Activation module notifying emergency services or those responsible in critical cases that require immediate intervention. Furthermore, other modules can be added to enhance intervention coverage, such as managing medication, supporting physical activity, and monitoring emotional states.

6. Usage Scenarios

The proposed model and software architecture were designed to enable continuous and less intrusive monitoring of Quality of Life. This section uses some scenarios to exemplify their applicability. The aim is to demonstrate the adherence of them to applications known in the literature and the industry.

Two applications were selected to illustrate the use cases. The criteria for selection were representativeness and suitability for the proposed artifacts. The first one is Google Fit[2], a commercial application with high market relevance and well-established. The other application was an application proposed by the literature: QoLES [14].

Google Fit is a health and fitness tracking platform developed by Google that monitors users' general health and physical activities using built-in activity trackers in mobile devices and wearables, such as walking, running, and cycling. It also allows integration with many other health applications and devices.

Through the implementation based on the proposed model and architecture, Google Fit could be enhanced with advanced QoL monitoring functionalities. While maintaining its existing features, such as tracking physical activity and monitoring sleep patterns, the platform could be expanded in the Monitor stage to capture more comprehensive indicators like daily mobility, physical activity levels, sleep quality, and others.

The data extraction would be done through various sensors integrated into the platform, capturing information via smartwatches, fitness bands, heart rate monitors, and smartphones. These devices, capable of integrating with Google Fit, would provide a wide range of contextual data, such as heart rate, sleep patterns, and physical activity levels.

[2]Google Fit: google.com.br/fit

Even so, it's important to highlight the limitations of Google Fit. In its current form, it already collects a significant amount of data through embedded sensors, but the platform was not originally designed to make complex inferences about users' mental or emotional health status.

However, implementing clustering algorithms such as Self-Organizing Maps (SOM) could group the data into different contexts and, after this clustering stage, professionals analyzing the data would label the groups. Subsequently, the health status data, grouped using these clusters, would be used to train machine learning algorithms. In this way, it would be possible to develop an instrument based on contextual data capable of inferring users' health status.

SOM can be viewed as a nonlinear extension of classical Principal Component Analysis (PCA) and Multidimensional Scaling (MDS) is frequently used for pattern clustering [14]. Compared to other techniques, such as PCA, SOM detects behavioral changes quickly and efficiently, allowing the identification of abnormal patterns [14]. The choice of SOM over other techniques is based on its ability to generate visual results that are easy to interpret and because it is an unsupervised learning technique that allows continuous monitoring and pattern detection over time, an essential function in the context of healthcare.

In addition, after the Data Polish stage in the analysis, the data can be enriched with external information, such as meteorological or environmental data, during the Data Enrichment phase. This integration improves subsequent processing by machine learning algorithms, allowing for more accurate inference of QoL indicators in the Self-Service Machine Learning stage.

Furthermore, by using other meta-attributes from data enrichment, it would be possible to establish rules that validate the quality of the data acquired for Knowledge. Moreover, the risk analyzer could be used as a simplified version of the method proposed by [51], which explores what-if analysis to predict factors affecting adolescent obesity.

In this way, the platform could monitor more than just physical activity; it would be possible to display reports, graphs, and statistics and, at the same time, generate changes and notifications on the devices integrated into Google Fit and other interventions integrated into a smart environment via the worker modules with a more robust intervention plan.

Regarding QoLES, it assesses the QoL of elderly and disabled individuals using a smart environment equipped with sensors and connected appliances. It analyzes contextual data to provide QoL reports to caregivers, but it also has its limitations. This platform relies heavily on environmental sensors and advanced technological infrastructure, which may restrict its applicability in environments where such infrastructure is unavailable or difficult to maintain.

The proposed model and architecture address these limitations by enabling more flexible data collection and processing. By utilizing the suggested data extraction interface in the monitoring phase, the system allows for the scalable and flexible implementation of various data capture methods across multiple devices. Additionally, the analysis phase modules can be extended and adapted, further reducing the dependency on advanced infrastructure.

During the QoLES analysis stage, similar to Google Fit, SOM is already used for pattern recognition and analysis of large data sets. However, unlike the current version of QoLES, the proposed model for inferring QoL would not rely on domain experts to interpret the results in the Self-Service Machine Learning module. This could be achieved by enriching data and context and establishing quality assessment rules with periodic evaluation.

Additionally, using the same strategy mentioned earlier in Google Fit, in the plan stage, it would be possible to develop an intervention plan that could, during the Execution phase, assist in medical care decision-making, such as recommending noise-canceling headphones or creating quiet zones.

From what has been discussed, it can be seen that the proposed analytical model and software architecture are suitable for the context of continuous and less intrusive QoL monitoring. The scenarios presented show the flexibility and applicability of these artifacts in different usage scenarios, thus demonstrating their capacity to integrate with various devices and systems for collecting and analyzing contextual data. In addition, the scenarios emphasize that the model and architecture can be extended and adapted to suit different contexts of use.

7. Final Remarks

This paper proposed an analytical model and a software architecture for Quality of Life (QoL) based systems in the context of IoHT.

The proposed analytical model uses logical reasoning to model system entities and specify their relationships. It outlines the interactions between the user, the environment, and system elements. The model uses IoT devices to sense the environment and the user, capturing data that is then passed on to other entities within the model. These entities can use the data to generate interventions in specific contexts to enhance the QoL. The entities can be instantiated in various solutions to meet different needs, and the flows can be extended to further improve the responsiveness of QoL-based systems.

The proposed architecture was inspired by the MAPE-K reference model used to implement loops for Self-Adaptive Systems; however, its focus is not on creating SAS but on the adaptation caused in the user's environment to improve their QoL. The architecture consists of four modules: Monitor, Analyze, Plan, and Execute. The flow begins with the extraction of user data by the Monitor, followed by the analysis and processing of the data, which is used to generate a QoL report, used in the planning phase to assess risks and create an intervention plan, which is then executed by the work module that triggers the necessary interventions in the user environment.

Moreover, this study includes practical use cases to demonstrate the model's alignment with the architecture and its applicability to real-world applications. To achieve this, two well-suited and representative applications were selected: Google Fit and QoLES.

To conclude, we argue that this study can significantly benefit both professionals and researchers. For professionals, the proposed analytical model and architecture offer a practical, ready-to-use solution encompassing overall management within QoL-based systems. Additionally, the adaptability of these artifacts allows for customization and extension to suit various applications, enhancing their utility across diverse real-world scenarios. For researchers, this work serves as a foundational contribution, providing a starting point for future research on QoL-based systems. The proposed artifacts address the existing gap and pave the way for developing more sophisticated and integrated systems. Subsequent studies can build upon this work, using the analytical model and architecture as essential tools to explore new dimensions and innovations at the intersection of IoHT and QoL.

Looking ahead, another research opportunity would be developing a system capable of automating the foundational construction of IoHT QoL-based systems. Leveraging the needs provided, such as entities defined, this system could automatically generate the core structure of a QoL monitoring system. This would streamline the initial setup process and ensure consistency and alignment with best practices.

Acknowledgments

We acknowledge that the development of the PARTNER platform was made possible through a collaborative effort and research project. It was developed as results of an R&D project funded by the startup GoTest and the Fundação Cearense de Pesquisa e Cultura.

References

[1] L. Atzori, A. Iera, G. Morabito, The internet of things: A survey, Computer networks 54 (2010) 2787–2805.
[2] S. Kumar, P. Tiwari, M. Zymbler, Internet of things is a revolutionary approach for future technology enhancement: a review, Journal of Big data 6 (2019) 1–21.
[3] J. Haughey, K. Taylor, M. Dohrmann, G. Snyder, Medtech and the internet of medical things: How connected medical devices are transforming health care, Deloitte (2018) 112.
[4] A. Asghar, A. Abbas, H. A. Khattak, S. U. Khan, Fog based architecture and load balancing methodology for health monitoring systems, IEEE Access 9 (2021) 96189–96200.

[5] J. J. Rodrigues, D. B. D. R. Segundo, H. A. Junqueira, M. H. Sabino, R. M. Prince, J. Al-Muhtadi, V. H. C. De Albuquerque, Enabling technologies for the internet of health things, Ieee Access 6 (2018) 13129–13141.
[6] T. N. Gia, M. Ali, I. B. Dhaou, A. M. Rahmani, T. Westerlund, P. Liljeberg, H. Tenhunen, Iot-based continuous glucose monitoring system: A feasibility study, Procedia Computer Science 109 (2017) 327–334.
[7] W. Group, The development of the world health organization quality of life assessment instrument (the whoqol), in: Quality of Life Assessment: International Perspectives: Proceedings of the Joint-Meeting Organized by the World Health Organization and the Fondation IPSEN in Paris, July 2–3, 1993, Springer, 1994, pp. 41–57.
[8] V. Estrada-Galinanes, K. Wac, Visions and Challenges in Managing and Preserving Data to Measure Quality of Life, in: 2018 IEEE 3rd International Workshops on Foundations and Applications of Self* Systems (FAS*W), IEEE, Trento, 2018, pp. 92–99. doi:10.1109/FAS-W.2018.00031.
[9] K. K. V. Mate, Using New Technologies in Quality of Life Assessment, in: A. P. Kassianos (Ed.), Handbook of Quality of Life in Cancer, Springer International Publishing, Cham, 2022, pp. 123–131. doi:10.1007/978-3-030-84702-9_8.
[10] T. N. Gia, A.-M. Rahmani, T. Westerlund, P. Liljeberg, H. Tenhunen, Fault tolerant and scalable iot-based architecture for health monitoring, in: 2015 IEEE Sensors Applications Symposium (SAS), IEEE, 2015, pp. 1–6.
[11] A. Taivalsaari, T. Mikkonen, A roadmap to the programmable world: software challenges in the iot era, IEEE software 34 (2017) 72–80.
[12] IEEE Committee, IEEE Standard Glossary of Software Engineering Terminology, Technical Report, IEEE, United States, 1990. doi:10.1109/IEEESTD.1990.101064.
[13] R. S. Pressman, Software engineering: a practitioner's approach, 7th ed ed., McGraw-Hill Higher Education, New York, 2010.
[14] A. Bono-Nuez, R. Blasco, R. Casas, B. Martín-del Brío, Ambient intelligence for quality of life assessment, Journal of Ambient Intelligence and Smart Environments 6 (2014) 57–70.
[15] A. M. Rahmani, T. N. Gia, B. Negash, A. Anzanpour, I. Azimi, M. Jiang, P. Liljeberg, Exploiting smart e-health gateways at the edge of healthcare internet-of-things: A fog computing approach, Future Generation Computer Systems 78 (2018) 641–658.
[16] IBM, An architectural blueprint for autonomic computing, IBM White Paper 31 (2006) 1–6.
[17] M. Salehie, L. Tahvildari, Self-adaptive software: Landscape and research challenges, ACM transactions on autonomous and adaptive systems (TAAS) 4 (2009) 1–42.
[18] L. Malburg, M. Hoffmann, R. Bergmann, Applying mape-k control loops for adaptive workflow management in smart factories, Journal of Intelligent Information Systems 61 (2023) 83–111.
[19] M. A. Naqvi, M. Astekin, S. Malik, L. Moonen, Adaptive immunity for software: Towards autonomous self-healing systems, in: 2021 IEEE International Conference on Software Analysis, Evolution and Reengineering (SANER), IEEE, 2021, pp. 521–525.
[20] J. Ellen, H. Li, M. D. Ohman, Quantifying California current plankton samples with efficient machine learning techniques, IEEE, 2015.
[21] F. Yang, Q. Wu, X. Hu, J. Ye, Y. Yang, H. Rao, R. Ma, B. Hu, Internet-of-things-enabled data fusion method for sleep healthcare applications, IEEE Internet of Things Journal 8 (2021) 15892–15905.
[22] H. Pandzic, Y. Dvorkin, D. Kirschen, R. Fernandez-Blanco, J.-P. Watson, C. Silva-Monroy, Ensuring profitability of energy storage, in: 2017 IEEE Power & Energy Society General Meeting, IEEE, 2017, pp. 1–1.
[23] I. Alfonso, K. Garcés, H. Castro, J. Cabot, Self-adaptive architectures in iot systems: a systematic literature review, Journal of Internet Services and Applications 12 (2021) 1–28.
[24] J. P. Queralta, T. N. Gia, H. Tenhunen, T. Westerlund, Edge-ai in lora-based health monitoring: Fall detection system with fog computing and lstm recurrent neural networks, in: 2019 42nd international conference on telecommunications and signal processing (TSP), IEEE, 2019, pp. 601–604.
[25] A. Ilyas, M. N. Alatawi, Y. Hamid, S. Mahfooz, I. Zada, N. Gohar, M. A. Shah, Software architecture

for pervasive critical health monitoring system using fog computing, Journal of Cloud Computing 11 (2022) 84.
[26] J. Son, Y. Kim, S. Zhou, Alerting patients via health information system considering trust-dependent patient adherence, Information Technology and Management 23 (2022) 245–269.
[27] F. Azuaje, J. Dopazo, Data analysis and visualization in genomics and proteomics, Wiley Online Library, 2005.
[28] M. Malek, The art of creating models and models integration, in: International Workshop on Model-Based Software and Data Integration, Springer, 2008, pp. 1–7.
[29] A. Abran (Ed.), SWEBOK: guide to the software engineering body of knowledge, version 3.0 ed., IEEE Computer Society, Los Alamitos, CA, 2014.
[30] S. Friedenthal, A. Moore, R. Steiner, Chapter 18 - integrating sysml into a systems development environment, in: S. Friedenthal, A. Moore, R. Steiner (Eds.), A Practical Guide to SysML (Third Edition), The MK/OMG Press, third edition ed., Morgan Kaufmann, Boston, 2015, pp. 507–541. doi:10.1016/B978-0-12-800202-5.00018-7.
[31] P. A. Oliveira, R. Andrade, P. Santos Neto, Lessons Learned from mHealth Monitoring in the Wild, in: Proceedings of the 16th International Joint Conference on Biomedical Engineering Systems and Technologies, Lisbon, Portugal, 2023, pp. 155–166.
[32] N. Olson, J. M. Nolin, G. Nelhans, Semantic web, ubiquitous computing, or internet of things? a macro-analysis of scholarly publications, Journal of Documentation (2015).
[33] C. D. McNaughton, A. McConnachie, J. G. Cleland, J. A. Spertus, C. E. Angermann, P. Duklas, J. Tromp, C. S. Lam, G. Filippatos, U. Dahlstrom, et al., Quality of life assessed 6 months after hospitalisation for acute heart failure: an analysis from report-hf (international registry to assess medical practice with longitudinal observation for treatment of heart failure), European Journal of Heart Failure (2022).
[34] A. De Masi, M. Ciman, M. Gustarini, K. Wac, mQoL smart lab: quality of life living lab for interdisciplinary experiments, in: Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing Adjunct, ACM, Heidelberg Germany, 2016, pp. 635–640. doi:10.1145/2968219.2971593.
[35] P. Oliveira, R. Andrade, P. S. Neto, Healful - internet of health things platform to monitor quality of life, in: Anais Estendidos do XXIV Simpósio Brasileiro de Computação Aplicada à Saúde, SBC, Porto Alegre, RS, Brasil, 2024, pp. 109–114. URL: https://sol.sbc.org.br/index.php/sbcas_estendido/article/view/28713.
[36] S. Schmidt, M. Power, M. Bullinger, A. Nosikov, The conceptual relationship between health indicators and quality of life: results from the cross-cultural analysis of the eurohis field study, Clinical Psychology & Psychotherapy: An International Journal of Theory & Practice 12 (2005) 28–49.
[37] T. Vetrovsky, J. Cupka, M. Dudek, B. Kuthanova, K. Vetrovska, V. Capek, V. Bunc, et al., Mental health and quality of life benefits of a pedometer-based walking intervention delivered in a primary care setting, Acta Gymnica 47 (2017) 138–143.
[38] J. Vallance, D. Eurich, P. Gardiner, L. Taylor, S. Johnson, Associations of daily pedometer steps and self-reported physical activity with health-related quality of life: results from the alberta older adult health survey, Journal of aging and health 28 (2016) 661–674.
[39] W. E. Kraus, K. F. Janz, K. E. Powell, W. W. Campbell, J. M. Jakicic, R. P. Troiano, K. Sprow, A. Torres, K. L. Piercy, . P. A. G. A. Committee, et al., Daily step counts for measuring physical activity exposure and its relation to health, Medicine and science in sports and exercise 51 (2019) 1206.
[40] R. M. Panicker, B. Chandrasekaran, "wearables on vogue": a scoping review on wearables on physical activity and sedentary behavior during covid-19 pandemic, Sport Sciences for Health (2022) 1–17.
[41] W. Sanchez, A. Martinez, W. Campos, H. Estrada, V. Pelechano, Inferring loneliness levels in older adults from smartphones, Journal of Ambient Intelligence and Smart Environments 7 (2015) 85–98.
[42] L. Dahlberg, K. J. McKee, A. Frank, M. Naseer, A systematic review of longitudinal risk factors for loneliness in older adults, Aging & Mental Health 26 (2022) 225–249.

[43] R. Mushtaq, S. Shoib, T. Shah, S. Mushtaq, Relationship between loneliness, psychiatric disorders and physical health? a review on the psychological aspects of loneliness, Journal of clinical and diagnostic research (JCDR) 8 (2014) WE01.

[44] F. S. Luyster, P. J. Strollo, P. C. Zee, J. K. Walsh, Sleep: a health imperative, Sleep 35 (2012) 727–734.

[45] S. L. Worley, The extraordinary importance of sleep: the detrimental effects of inadequate sleep on health and public safety drive an explosion of sleep research, Pharmacy and Therapeutics 43 (2018) 758.

[46] J. Stojanov, M. Malobabic, G. Stanojevic, M. Stevic, V. Milosevic, A. Stojanov, Quality of sleep and health-related quality of life among health care professionals treating patients with coronavirus disease-19, International Journal of Social Psychiatry 67 (2021) 175–181.

[47] A. Arora, P. Chakraborty, M. Bhatia, Analysis of data from wearable sensors for sleep quality estimation and prediction using deep learning, Arabian Journal for Science and Engineering 45 (2020) 10793–10812.

[48] E. Gamma, R. Helm, R. Johnson, J. Vlissides, Design Patterns: Abstraction and Reuse of Object-Oriented Design, in: ECOOP' 93 — Object-Oriented Programming, volume 707, Springer Berlin Heidelberg, Berlin, Heidelberg, 1993, pp. 406–431.

[49] E. Gamma, Design patterns: Elements of reusable object-oriented software, 1995.

[50] M. Shaw, D. Garlan, Software architecture: perspectives on an emerging discipline, Prentice-Hall, Inc., 1996.

[51] C. Kim, F. J. Costello, K. C. Lee, Y. Li, C. Li, Predicting factors affecting adolescent obesity using general bayesian network and what-if analysis, International journal of environmental research and public health 16 (2019) 4684.