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Research Paper

A Platform for Remote Monitoring of Older Adults: The Value of Heart Rate Variability

Eujessika Rodrigues [Universidade Federal do Rio Grande do Norte | *eujessika.rodrigues@nutes.uepb.edu.br*]
Paulo Barbosa [Universidade Estadual da Paraíba | *paulo.barbosa@nutes.uepb.edu.br*]
Daniella Carvalho [Universidade Estadual da Paraíba | *daniella.lima@nutes.uepb.edu.br*]
Elisa Nakagawa [Universidade de São Paulo | *elisa@icmc.usp.br*]
Sabrina Fernandes [Universidade Federal do Rio Grande do Norte | *sabrinafernandes@gmail.com*]
Ana Tereza Fernandes [Universidade Estadual da Paraíba | *aninhat.sales@gmail.com*]
Álvaro Maciel [Universidade Federal do Rio Grande do Norte | *alvarohuab@ufrnet.br*]
Lina Garcés [Universidade de São Paulo | *linagarces@usp.br*]

Núcleo de Tecnologias Estratégicas em Saúde - NUTES, Universidade Estadual da Paraíba - UEPB, Av. Juvêncio Arruda, S/N - Universitário, Campina Grande - PB, 58429-600, Brazil.

Abstract. Background: Despite the inherent disabilities of human aging, the number of older adults is growing. Previous works have proposed and explored technologies to improve the quality of life of older adults and mitigate this challenge in the health field. In particular, technologies based on Heart Rate Variability (HRV), measure the decrease of vagal tone and sedentary behaviors in age. Although this measure can be used remotely in older adults' care, it has been only made available for clinical testing environments, laboratories, and hospitals. To address this gap, in this paper, we present Senior Mobile Health (SMH), a platform that supports the development of a complete system composed of mobile apps deployed in wearables and web systems for the remote monitoring of the HRV data of older adults. Results: We conducted a real-world case study with 89 older adults using the SMH and validated the results by comparing them with those provided by a reference clinical tool, the Kubios HRV. Conclusions: Our results show evidence that SMH aggregates an important value to older adults' care assisting in rehabilitation processes by health professionals.

Keywords: Heart Rate Variability; remote monitoring; aging; assistive technology; software architecture.

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1 Introduction

The increasing number of older adults has become one of the biggest challenges in the health field, affecting countries all around the world. For instance, in 2017, there were over 982 million old adults in the world; this number will increase to around 1.6 billion by 2030 (United Nations, 2017). As the aged population, the diseases and disabilities present in this aging process grow, the health field faces continuous changes. This way, advances are necessary to promote better services to this population (IBGE, 2018; Melo *et al*., 2018).

In this scenario, health technologies have become more and more present in therapeutic, diagnostic, and monitoring modalities. They have had a core role in the life quality of older adults (Antoniou *et al*., 2017). Examples of these technologies are presented in Garcia-Moreno *et al*. (2020); Lee *et al*. (2018); and Razjouyan *et al*. (2018). In particular, we can also find a specific set of technologies, having as the most referred Kubios HRV, besides Kandel and LabChart from Adinstruments, which can analyze the Heart Rate Variability (HRV). The HRV can indicate a decrease in vagal tone due to human aging and sedentary behaviors (Almeida-Santos *et al*., 2016). This way, it means monitoring HRV is required to provide a better quality of life for older adults. However, the aforementioned technologies are only suitable for use in clinics, hospitals, and test environments (Graham *et al*., 2019); they are not suitable for remote monitoring scenarios, such as in the current pandemic when older adults might be isolated and unassisted. The value of remotely measuring and analyzing the HRV data of the older adult has been left aside.

In this paper, we present an evolution and refinement of the Senior Mobile Health (SMH) platform (Rodrigues *et al*., 2022), with a broader case study involving 89 older adults to evaluate the feasibility and performance of SMH to calculate and predict HRV, i.e., three cardiac modulation indices in the time domain, in comparison to the gold standard HRV analysis software, Kubios. Previously, in (Rodrigues *et al*., 2022), we had recruited only ten older adults for convenience due to the pandemic constraints to focus on the development and initial validation of HRV features in the SMH. Technologically, this work also offers the SMH software architecture and its main features to show the challenges of collecting and treating HRV data from wearable devices. We designed a microservices solution for the Internet of Things (IoT) paradigm focused on HRV for remote health monitoring of older adults. The results indicate that the outcomes obtained by SMH are equivalent to the gold standard solution, suggesting that the two methods can be used interchangeably.

This paper is organized as follows. The second section presents a literature review of HRV monitoring. The third section summarizes the methodology of this research. The fourth section describes the process of screening older adults as the motivation for the technological development of this research. The fifth section details SMH as a software platform. The sixth section presents the case study for validating the HRV features. The seventh section presents a validation through a case study and discusses the main findings of this work. Finally, the last section concludes this work.

2 Literature Review

In this section, we performed a literature review for a better understanding of the current literature regarding HRV monitoring and analyzed the devices currently available to ensure the decision to use smartwatches.

HRV is measured by the consecutive interval between heartbeats modulated by the activity of the autonomic nervous system and its interaction with the cardiovascular system. The constant oscillations present in a heartbeat allow the cardiovascular system to quickly adjust to the intrinsic and extrinsic conditions that surround the individual, seeking to establish the necessary homeostasis for sudden physical, psychological, or emotional changes, as well as the changes inherent in the process of human aging (Forte *et al*., 2019; Shaffer and Ginsberg, 2017).

Data indicates that low HRV may be related to adverse health outcomes and mortality after suffering a cardiovascular event, such as a myocardial infarction. In addition, several studies have associated cognitive dysfunctions, especially those related to age, with low HRV values. The changes presented in cognitive functions, through adverse autonomic conditions, can be reflected in the autonomous control of the heart. In this context, the intimate interaction between HRV and cognitive functioning has been the object of study among researchers to analyze HRV in the search for early identification of changes in this health indicator in the elderly population (Forte *et al*., 2019; Shaffer and Ginsberg, 2017; Chen *et al*., 2019)

Several studies also suggest a close relationship between low rates of HRV with age, pointing out that naturally with advancing age, HRV tends to decrease. However, as described in Tan *et al*. (2019), this association is still unclear, suggesting that this association can be found due to sample recruitment, which in many studies is aimed at older adults with physical and cognitive disorders. It also indicates the need for longitudinal studies, following healthy individuals for prolonged periods, to accurately assess these relationships and explore individual autonomic changes (Tan *et al*., 2019).

In recent years, in addition to studies related to the understanding of HRV indicators and their relationship with health disorders and age, the research has aimed at potential tools for analyzing this indicator. Traditionally, HRV is assessed using devices such as the electrocardiogram (ECG) or Holter monitoring performed within a clinical environment, totally outside the individual's regular routine, for short periods and cross-sectional analyses (Graham *et al*., 2019; Natarajan *et al*., 2020). However, other tools have emerged such as HRV assessment mechanisms acting within a simpler context, which can be inserted into the individual's regular routine and with reduced costs. Devices based on photoplethysmography (PPG) sensors, positioned on the user's wrist, use the wavelength of light through the skin to measure reflected light, thus detecting the volume within blood vessels and measuring changes in light absorption; these changes reflect the heartbeat. This type of device, minimally invasive, allows the possibility of capturing Heart Rate (HR) data for long periods (Graham *et al*., 2019; Natarajan *et al*., 2020).

In addition to devices that capture HR data, tools that store this data and transform it into HRV information are needed. Currently, software such as Kubios offers this functionality, receives short HR data via ECG and Holter, and displays HRV data to the health professional. Platforms such as Kubios act only in the context of HRV, and it is not possible to store other types of health data, such as sleep data, and physical activity, among others, which are important to be evaluated longitudinally when aiming to assess HRV for older adults.

3 Method

Figure 1 shows the four steps that conducted this research. Each step is described in the following sections. Step 1 was the main motivation for the technological development since we observed a high need for remote monitoring when tracking older adults using the Elderly Health Handbook. In Step 2, we took the initiative of developing the SMH as a software platform, a tool that is already monitoring hundreds of older adults and generating data for geriatric research. We made decisions about its features, software architecture, and device integration. In Step 3, we focused on developing the HRV features, calculating the main HRV indices from data captured from a PPG sensor in Fitbit devices. Finally, the last step of this methodology focuses on a case study for validating the reliability of HRV metrics with 89 older adults, a larger number of participants if compared to the validation provided in Rodrigues *et al*. (2022). We performed descriptive statistics and clustering analysis comparing HRV metrics calculated in the SMH with those calculated in the Kubios HRV.

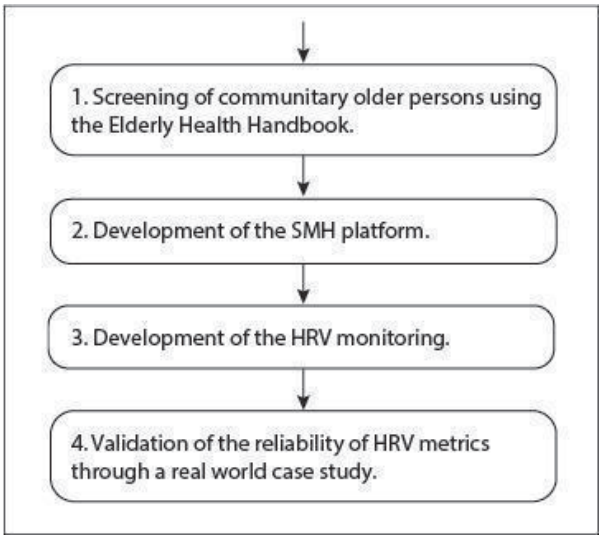


Figure 1. The four steps of the methodology.

4 Screening of Older Adults Using the Elderly Health Handbook

Among the set of initiatives established by the Brazilian government to improve the health management of the elderly is the implementation of the Elderly Health Handbook. This instrument is intended to identify particularities, vulnerabilities, and weaknesses, as well as to promote specific actions aimed at comprehensive care, improving quality of life, and reducing mortality in the older adult population (Ministério da Saúde do Brasil., 2018).

In this perspective, protocols that add a comprehensive assessment of the elderly can bring benefits in promoting the health of this population, as in the case of the study we previously coordinated entitled Pro-Eva (Promotion of Aging and Active Life). Its main objective was to strengthen the use of the Elderly Health Handbook to improve care for the older adult in a municipality in the Brazilian Northeast (Gonçalves *et al.*, 2023).

This project identified opportunities for the inclusion of technologies that could integrate information from the Elderly Health Handbook with that collected by wearables and processed in a platform for remote monitoring. With a structured baseline, the opportunity arose for the remote monitoring to capture HRV data to establish possible relationships between variability and information from the instrument and thus establish hypotheses for the decline in the health of older adults. Since the beginning of the project, more than a thousand older adults have been recruited and monitored using the Elderly Health Handbook.

Once the SMH was developed to encompass other measurements collected remotely, a new opportunity arose to build more robust HRV features, as reported in this work.

5 SMH Platform

This section presents the main features of SMH, its context, and its software architecture. It also gives a detailed explanation of the HRV calculation, which is the core feature of the SMH. This section also illustrates its main user interfaces.

5.1 Main Features and Context

The main users of the SMH are health professionals (e.g., geriatrics and physiotherapists) and caregivers that provide health monitoring services for older adults. Other core users of this platform are older adults, who use wearable devices deployed with a mobile app that encourages them in their self-care by establishing specific goals and activities.

The main feature of SMH is the monitoring of HR besides other health indicators, medicines, frailty analysis, daily progress, gait speed, and risk of falling (Palestra *et al.*, 2017). Using sensors, such as accelerometers and photoplethysmography, to analyze the movements and steps during the night, the SMH can identify how often the individual wakes up at night and goes to the bathroom, for example. With this information, health professionals can guide older adults to investigate their clinical conditions and organize the environment to avoid falls or other risks. In particular, nocturia is a condition in which an individual wakes up at night one or more times to urinate. Each urination is preceded and followed by a period of sleep. This condition is recurrent in older adults due to factors inherent in the aging process (Vaughan and Bliwise, 2018).

Step counter sensors such as accelerometers can provide daily monitoring of the activity level and the number of steps taken per day. They can also be used as a strategy to motivate older adults to remain active through goals established by health professionals. Recent studies show how many steps a day are enough for specific populations such as older adults to be considered active and free of chronic diseases (Tudor-Locke *et al.*, 2011).

Thereby, using SMH, patients are monitored, and specific profiles are created, allowing the health professionals to accompany their patients.

The gait speed has been used as another important metric to monitor the health of older adults. Changes in the gait speed patterns can be markers of various general medical conditions, including cognitive decline, leading to an increased chance of falls, hospitalizations, or even death. The high association between gait speed and the adverse clinical outcome becomes this measure important information and is used by health professionals (Abellan van Kan *et al.*, 2009; Binotto *et al.*, 2018). However, the measure of gait speed is sometimes collected manually by health professionals and then calculated. The SMH can automatically obtain this information from wearable devices, facilitating the work of health professionals.

The synchronization of data is an essential feature of SMH. Data collected from various wearable devices that are sent to a provider server is converted into a model accepted by SMH. SMH also provides a time series analysis to monitor data on the health of older adults. For that, SMH encompasses machine learning algorithms to predict adverse health outcomes and promote real-time and continuous monitoring of the users.

5.2 Software Architecture

The software architecture of the SMH is based on microservices and IoT, reusing our previous experiences with the implementation of healthcare services (Barbosa *et al.*, 2020b) and an IoT-based architecture (Barbosa *et al.*, 2020a). Figure 2 shows the SMH software architecture composed of nine core components:

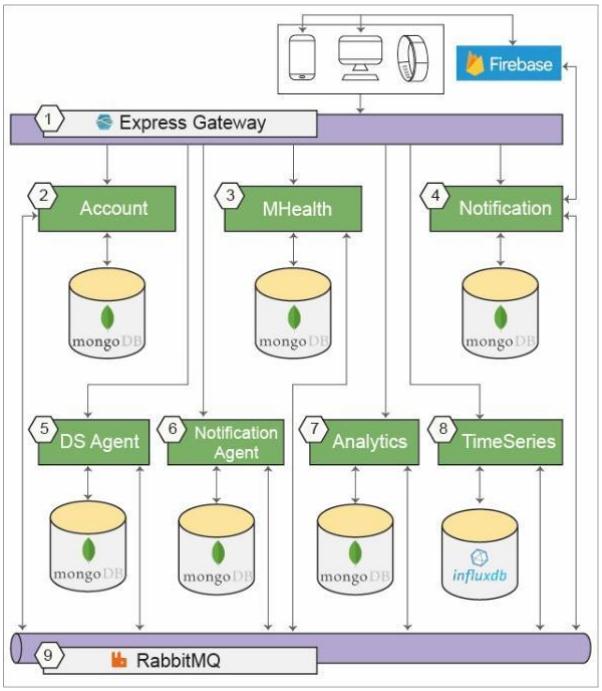


Figure 2. The software architecture of the SMH.

- Express Gateway: The API Gateway, is the unique component exposed to the external network. It is responsible for exposing endpoints to the clients (i.e., for the mobile apps and web system) and for working as a proxy to the internal microservices;

- Account: Microservice responsible for the authentication and storage of general user information;
- MHealth (Measurement of Health data): Microservice in charge of storing measurements of HRV, weight, blood pressure, physical activity, and sleep, among others;
- Notification. Microservice responsible for sending e-mails and SMS and pushing messages using Firebase Cloud Message for web systems and mobile devices;
- DS Agent (Data Synchronization Agent): Service in charge of external data synchronization (from wearable devices) with the SMH. A synchronization implies the user data capture in the external service, the preprocessing of data to convert it into the data model supported by the SMH, and also the data published in the message channel. After that, other microservices responsible for the data storage receive the data and save it in their database;
- Notification Agent: Microservice responsible for centralizing business rules and storing questionnaires;
- Analytics: Microservice responsible for the data processing and analysis and for supplying information related to older adult health;
- Time Series: Microservice responsible for the storage of time series, such as steps, calories, distance, active minutes, and HR; and
- RabbitMQ Message Channel: Message bus for the asynchronous communication among the microservices of the SMH.

In short, on top of Figure 2, web systems deployed on computers make it possible for health professionals to analyze data, manage perspective, and visualize synthesized data according to trends common to the aging process. In the meantime, applications deployed on mobile devices (smartphones) and wearable devices (smartwatches and smart bands) are responsible for collecting older adults' data and providing support to caregivers regarding their health status and engagement. In this sense, this solution does not involve the development of any new device for collecting user data but using devices provided by the main available brands that provide open APIs, such as Fitbit, Garmin, or Polar. In particular, the wearable device data is transmitted via Bluetooth to the application on the user's mobile device, which makes the necessary data processing and sends it to the wearable device provider server, where such data becomes available for consultation by third parties via web services. Due to the manufacturer's internal policies and security measures, third-party applications are not allowed to collect data directly from wearable devices. Therefore, the sole responsible for the collection is the application. After that, third-party applications can collect this data, if they have the appropriate permissions.

6 HRV Calculation

The HRV reflects the oscillations in the interval (in milliseconds) between consecutive heartbeats (i.e., RR intervals), which result mainly from the dynamic interaction between the parasympathetic and the sympathetic system that compose the autonomic nervous system. The changes in HRV patterns provide early information about the decline in health, mainly cognitive functioning. Efficient autonomic mechanisms provide a high HRV, meaning a good adaptation for intrinsic and extrinsic factors, an indicator of healthy individuals. On the other hand, a low HRV reflects abnormal adaptation and inefficiency of the autonomic nervous system. Therefore, HRV can be considered an early biomarker of cognitive impairment in the elderly population (Graham *et al*., 2019; Forte *et al*., 2019; Matos *et al*., 2020).

In particular, the time series are saved in the database in the shortest possible intervals. This paper only focuses on Fitbit because it has a different specification for the manipulation of times series compared to Garmin. With this, it is possible to make consultations by time series of 1 minute, 15 minutes, or a custom interval. Steps, calories, distance, and active minutes have the smallest spacing of 1 minute, and these series are saved in the database with values spaced of 1 minute. HR is characterized by consecutive heartbeats, being measured by counting the number of heartbeats per minute (bpm). In this case, HR has a smaller spacing of 1 second. This means that this time series has the HR value every 1 second (conceptually). On the other hand, it is worth mentioning that Fitbit devices save data with an interval of 1-N second, usually every 5 seconds, and, at this moment, it is a limitation of the manufacturer in all its devices.

Regarding querying, for the steps, calories, distance, and active minutes series, when a query is made with a space interval greater than the minimum of 1 minute, the sum between the intervals is performed. For HR, the minimum is 1 second, and the arithmetic mean between the intervals is performed. Fitbit or any other service applies the same approach.

Figure 3 presents the main steps of our HRV calculation. In Step 1, the data acquired from Fitbit that consists of the HR time series data with gaps (*i.e.*, missing data due to possible measurement failures) is filled in to guarantee its integrity. For that, we compared the performance of several different classical imputation methods through the Mean Squared Error (MSE), which determines the average of the squared difference between the original and the predicted values. A smaller MSE implies greater accuracy, ensuring that the data would be filled in in a satisfactory way (Chabot *et al*., 1991). Hence, we selected and implemented the PCHIP (Piecewise cubic Hermite interpolating polynomial) method, which presented an RMSE of 1.14 (Rodrigues *et al*., 2022).

Step 2 aims to approximate the data obtained from Fitbit to the data coming from ECG (electrocardiogram) sensors, the reference standard device for monitoring HR that directly measures the electrical signals produced by the heart activity, being able to capture more comprehensive signals than the PPG (photoplethysmogram) sensors present on wearable devices. For that, we applied different machine learning techniques (including Multinomial Logistic Regression, K Nearest Neighbors, Decision Tree, Random Forest, AdaBoost, Linear Regression, and Neural Networks) (Rodrigues *et al*., 2022) that seek to approximate the data obtained from wearable devices to the data coming from ECG sensors, assuming that there is an unknown underlying function that consistently maps those two. Following in Step 3, the Inter-beat Interval (IBI), also called RR interval, must be calculated. Traditionally, this is done by converting the raw HR data to IBI using the R-wave peak as the reference point. However, Fitbit does not provide the raw HR data, just the HR time series. As the

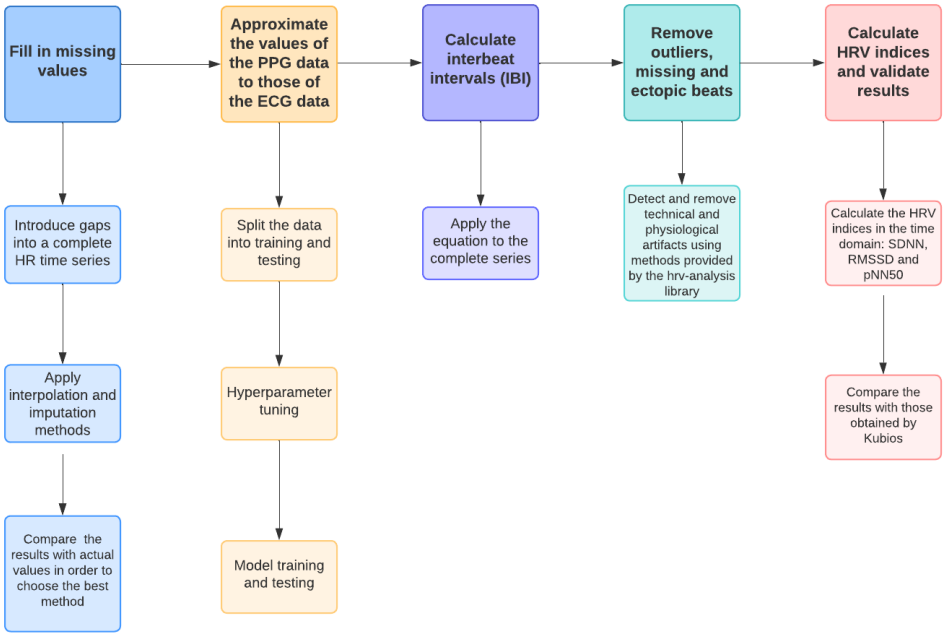


Figure 3. Main steps of the HRV calculation.

IBI is inversely related to HR, we used the following equation (Chabot *et al.*, 1991): $HR = 60000/IBI$.

In Step 4, the data is cleaned before applying any method for the HRV analysis, since any measurement in the time series can significantly interfere with such analysis. HRV artifacts (or measurements) can be divided into technical and physiological artifacts. Technical artifacts include missing or misaligned beats, while physiological artifacts include ectopic beats and arrhythmic events. Finally, in Step 5, the HRV time-domain indices are calculated and compared to the results obtained from Kubios.

This article mainly focuses on Steps 4 and 5. A detailed explanation of the remaining steps is fully described in Rodrigues *et al.* (2022).

To clean the data and remove the inconsistencies described in Step 4, we used the methods provided by the hrv-analysis library, distributed under the GPLv3 license. We first applied the outlier removal method. Following, we compared four different methods for removing ectopic beats, being:

- Malik Rule: IBIs differing by more than 20% from the one preceding it are removed;
- Karlsson Rule: IBIs diverging by more than 20% of the mean of previous and next IBI are removed;
- Kamath Rule: This method considers a heartbeat abnormal whenever the IBI increased by more than 32.5% or decreased by more than 24.5% when compared to the previous IBI; and
- Acar Rule: IBIs differing by more than 20% of the mean of the last nine IBIs are removed.

The adopted method was the Rodrigues *et al.* (2022) since it provided the most similar results to Kubios (the tool used as a reference) when we compared it with other methods. After that, in Step 5, we obtain the mean and its respective standard deviation of each IBI in a given time interval, which through mathematical techniques unfold in statistical indices that constitute the HRV analysis in the time domain.

We focus on the following HRV indicators: (i) SDNN (standard deviation of the interval between consecutive heartbeats); (ii) RMSSD (root mean square of successive heartbeats interval differences); and (iii) PNN50 (percentage of successive heartbeats intervals that differ by more than 50 milliseconds). Kubios also provide the calculations of these indicators. It is worth mentioning we included these indicators in SMH since long-term recordings (*e.g.*, 24 hours) can support healthcare professionals in assessing reactions of their patient's autonomic nervous system during normal daily activities and in response to therapeutic interventions, by comparing the patient's daily readings to determine if any significant changes have taken place (Wen and He, 2011).

6.1 User Interface for HRV

Figure 4 shows the screens of the app of SMH. From left to right, the first screen shows overall information collected by the wearable device, such as steps, active minutes, distance, calories, among others. The second screen shows the sleep data and records. The third screen shows one of the questionnaires and measurements that elderlies can manually insert. In particular, this screen shows questions about fatigue that can help calculate the frailty indicators of elderlies.

Figure 5 shows an excerpt of processing and displaying data in the web system. We deal with minimal time series intervals of 1 minute for HR, as shown in the figure. For other measurements, such as steps or calories, the intervals are 15 minutes. This possibility of manipulation is one of the main advantages of dealing with time series. The line presented in Figure 5 divides the *out-of-range* and *fat burn* classifications. Other examples of ranges are *normal* and *peak*. We have centrality and dispersion measurements for HR as minimum, mean, and maximum. HRV time-domain indexes (bottom in the figure) are SDNN, SDNN index, RMSSD, and PNN50.



Figure 4. Managing variables in the Senior Mobile Health App.



Figure 5. Expansion of the HRV indices for a specific day.

Figure 6 shows an excerpt of the web system user interface. It expands information about a specific month, offering another visualization option, *i.e.*, charts for all weeks of a month. This figure also shows the computed HRV metrics (SDNN index, SDNN, RMSSD, and PNN50) for the third and fourth weeks.

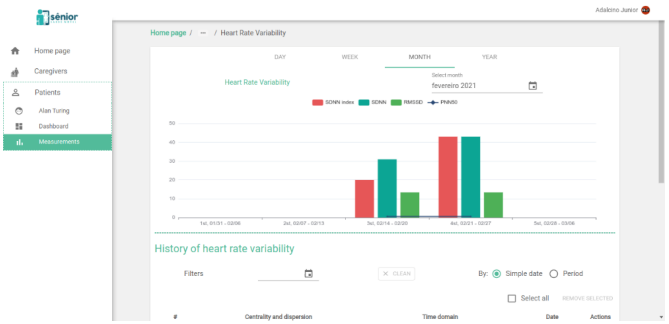


Figure 6. Monthly HRV chart.

7 Case Study and Results

The team of researchers that conducted this case study involved health professionals and data analysts. We addressed the following research question (RQ): *Can the SMH provide reliable HRV metrics?*

The sample of this research consisted of 89 community-dwelling individuals aged between 60 and 84 years, where 55 are women and 34 are men, in the city of Campina Grande (Brazil). All participants were invited by convenience. The participants who presented: (i) cognitive impairment assessed by the Leganés Cognitive Test following scores below the cut-off level for dementia (less than or equal to 22 points); (ii) those with severe visual problems; and (iii) those individuals bedridden, were excluded from the sample. All individuals involved were informed of the research objectives and procedures and signed the Free and Informed Consent Form. The study protocol was approved by the Ethics and Research Committee of the State University of Paraiba (approval number: 34702520.2.0000. 5187) and was performed following the Declaration of Helsinki.

The participants were requested to use a wearable device on the non-dominant wrist and keep their everyday activities. Data was collected 24 hours a day, and the participants were recruited from May 2020 to June 2022. During this period, the time series was saved on the SMH.

Figure 7 illustrates the design of our case study. We evolved the results presented in Wen and He (2011) with a more significant number of older adults with data already stored in the SMH. In short, in (1), we extracted the data of 89 older adults satisfying the criteria of having a 15-minute time series with no activity and no steps registered, the elderly at rest. This simulated the previous experiment in Wen and He (2011), where we collected data from older adults using Polar H10 chest straps in the resting state. Now the goal is to show the effectiveness of the SMH when conducting such HRV experiments without the chest strap device. After that, in (2), the SMH ran HRV algorithms to calculate the HRV metrics, including SDNN, RMSSD, and PNN50. In (3), we ran the data with Kubios algorithms, a reference HRV tool used in clinics, hospitals, and test environments. Finally, to answer our RQ, we compared the metrics after calculating the HRV metrics on the data collected from the 89 participants using both the SMH HRV algorithms and Kubios.

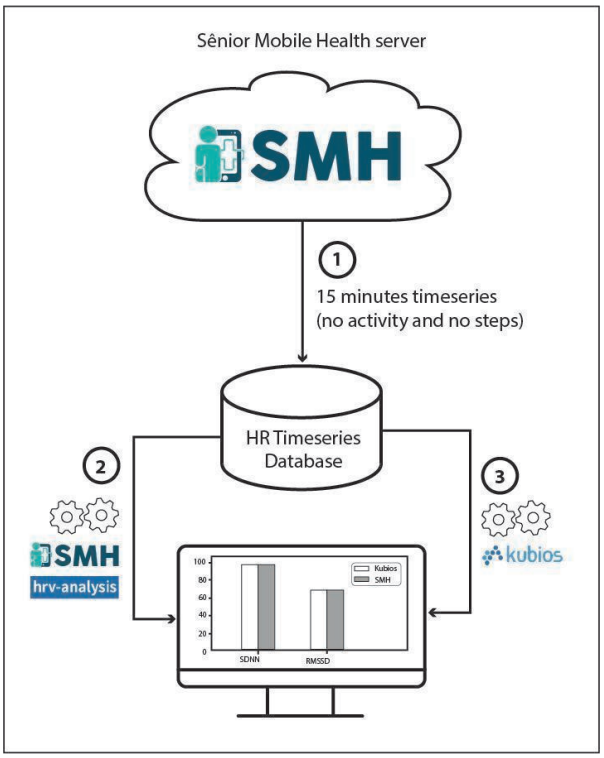


Figure 7. Case study for validation

The comparison of the boxplots for each metric shows that the data is distributed similarly in both SMH and Kubios. As the boxes overlap, there is no significant difference between them. Figures 8, 9, and 10 compare the SDNN, RMSSD, and pNN50, respectively, calculated by Kubios and SMH.

Additionally, as we intended to compare HRV metrics using two related paired observations on a single group of participants and our data did not follow a normal distribution,

we performed a Wilcoxon signed-rank test (Table 1) to determine whether the paired observations differed significantly from others.

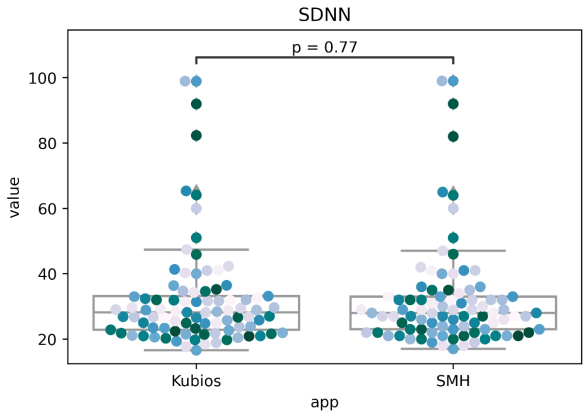


Figure 8. The standard deviation of all normal RR intervals (SDNN) for Kubios and SMH.

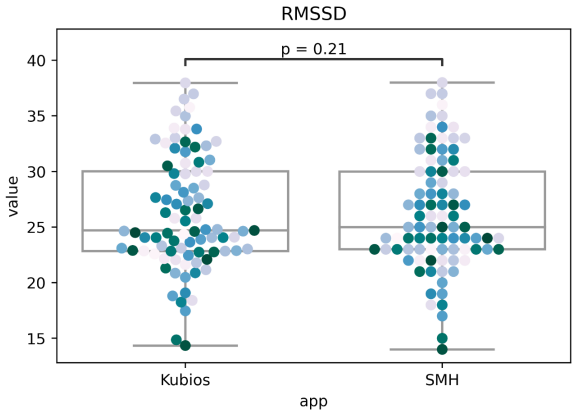


Figure 9. Root mean square of successive differences between normal heartbeats (RMSSD) for Kubios and SMH.

Using the significance level of 0.05, the p-value for SDNN was 0.211, which was greater than the significance level, so we accepted the null hypothesis that there is no change in SDNN with the usage of SMH. For RMSSD, the obtained p-value was 0.766, which is also greater than the significance level, so we accepted the null hypothesis. For pNN50, the p-value was 0.883, which is greater than the significance level, so we accepted the null hypothesis that there is no difference between the means. Thus, there is no difference between the results generated by the SMH and Kubios.

Table 1. Wilcoxon signed-rank test to check if there is any difference in the observations obtained using SMH in comparison with Kubios. Null Hypothesis: There is no change in the metric with the usage of SMH. Alternate Hypothesis: There is a change in the metric with the usage of SMH.

Metric	Statistic	p-value
SDNN	1697	0.211
RMSSD	1886.5	0.766
pNN50	1550	0.883

In addition, we used a graphical method to compare two measurement techniques, the Bland-Altman plot, which plots

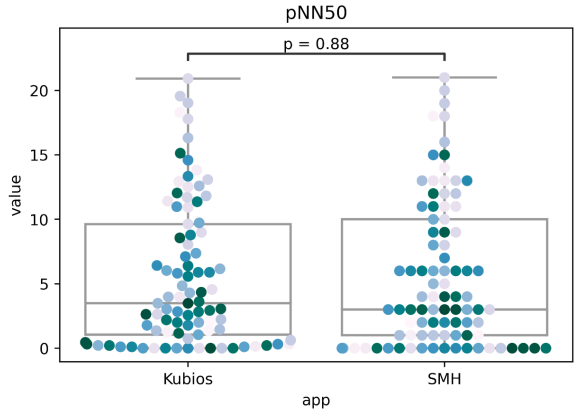


Figure 10. Results for the percentage of successive RR intervals that differ by more than 50 ms (pNN50) using Kubios and SMH.

the means of each pair of measurements versus the difference between the measurements. The horizontal lines represent the mean difference and the limits of agreement, defined as the mean difference ± 1.96 SD of differences. If the mean of the differences is close to zero and the limits are narrow, then the two methods are essentially equivalent, as for the three considered indexes, as shown in Figure 11, 12, and 13.

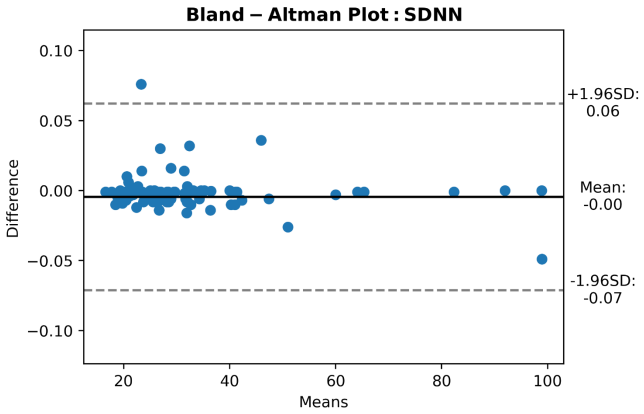


Figure 11. Bland-Altman plot for SDNN.

Lastly, to evaluate the HRV metrics resulting from the SMH and measure how far the values predicted by SMH are from the target output (*i.e.*, those calculated by Kubios), we computed the MSE, defined as the average of the square of the difference between actual and estimated values. This metric was chosen due to outliers in our data set and its popularity among evaluation metrics (Kleiger *et al.*, 2005). The MSE obtained was 0.0014. A small value of MSE indicates that our model fits well the target data. Summing up, the results found suggest that there is no significant difference between the values obtained by SMH in comparison with Kubios. Hence, we can conclude SMH can provide reliable results associated with HRV metrics and, therefore, health professionals could incorporate this platform during the remote monitoring of their patients.

Besides this quantitative analysis regarding the reliability of the results provided by SMH, we also conducted a qualitative analysis of the comfort of the participants while wearing watch-shaped devices. We noted a significant preference to use these devices compared with other obtrusive devices. The

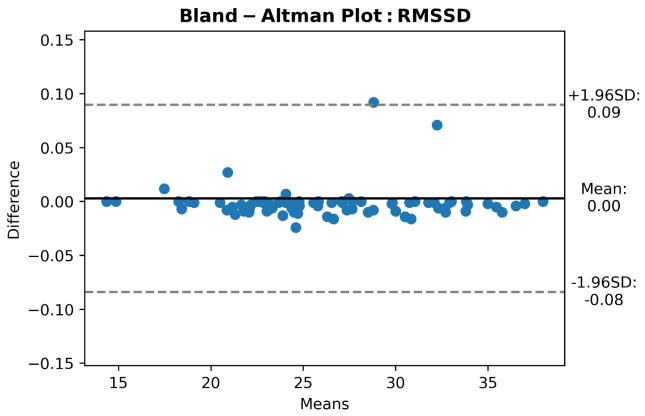


Figure 12. Bland-Altman plot for RMSSD.

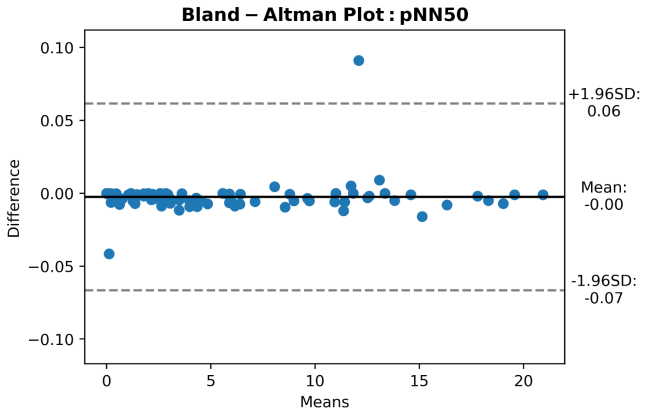


Figure 13. Bland-Altman plot for pNN50.

HRV metrics are traditionally measured in hospitals, clinics, and laboratories using ECG equipment or Holter monitor. These devices require expert setup, therefore, limiting their use and making it difficult for their daily use in the routine of older adults. Furthermore, these devices are considered more invasive when compared with wrist-worn devices, as they are allocated in the chest region through wires and fixation belts, providing a more unpleasant experience for users and making daily use impossible. Moreover, for health professionals, the acquisition of HRV metrics in the long-term through SMH can provide continuous following of older adults' health, early risk identification in their patients, and better conditions to follow the care for them.

8 Discussions

By delivering the SMH platform, we have received excellent feedback from health professionals and patients concerning improving the care services. It is worth highlighting that during the most critical period of the recent pandemic, this platform was essential due to the lack of mobility and vulnerabilities of patients. In addition to the need for all patients, even during the pandemic, they need to continue with their rehabilitation processes and this system was an excellent way to continue accompanying all the elderly during this period. The platform adoption has increased as new features have been completed and improvements in automatic feedback for patients and caregivers have become more evident.

Due to the results of HRV, we were able to initiate studies on geriatric syndromes and a better understanding of the levels of physical activity of the elderly according to what is available in the literature.

The SMH's microservice-based architecture allowed us to deliver continuously new services while keeping the platform fully operational. Many new requirements from the geriatric community emerged during the development of this platform. The combination of Express Gateway and the RabbitMQ message channel allowed us to keep good indicators of the quality attributes as the platform scaled.

We found that the capture of information on patients in different functional conditions 24 hours a day through wearable devices (smartwatches and smart bands) makes it possible for geriatrics and physiotherapists to provide a continuous evaluation of the health of the elderly, offering crucial data for the prediction of adverse health conditions and the rehabilitation processes. Moreover, the set of collected and predicted HRV data is trustworthy, since it is similar to results provided by a reference tool used in the clinical context.

The case study results also showed good perspectives that the SMH can provide reliable results besides using commercial wrist-worn wearable devices when compared with a setup accepted as the gold standard in the scientific community.

The main threat to the validity of the work is still the low sample used in the case study. Due to pandemic constraints, we were not able to design a study with a large number of participants. However, to mitigate this threat, we systematized the analysis of results, combining quantitative and qualitative analysis. Another threat is the lower frequency of HR measurements provided by Fitbit devices, as we usually have only one measurement for every 5 seconds. However, there is no other commercial device available and viable for the required use with lower latency according to our research. The process of filling in this data was presented in Rodrigues *et al.* (2022), and it was challenging in this work, where this constraint did not impact the overall results of HRV.

9 Conclusion

Software technologies can improve the quality of health services provided by health professionals and, more importantly, can effectively improve the patient's quality of life, including older adults. This paper contributes to a health technology that supports the remote monitoring of the health of the elderly. The main takeaway message of this work is that the calculation of HRV rates from elderly data collected remotely through commercial wearable devices is viable and reliable.

We also claim that the success of the development of health technologies depends directly on the full engagement of a multidisciplinary research team, including software developers, architects, testers, and data scientists, besides several health professionals in different specialties.

The SMH has been used in different health institutions, providing transparent, remote, and reliable health monitoring and prescription. At the same time, the high acceptance of this non-invasive technology by older adults is observed. Due to their value, we claim health technologies should be investigated, delivered, and adopted to contribute to healthy aging increasingly.

Declarations

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Authors' Contributions

Rodrigues, Barbosa, and Maciel conceived of the presented idea. Rodrigues, Fernandes, and Fernandes designed and performed the experiments. Carvalho, Nakagawa, and Garcés interpreted the results. Rodrigues, Barbosa, and Carvalho wrote the manuscript. All authors contributed to the design of the study, interpreted the data, and read and approved the final manuscript.

Competing interests

The authors have no relevant financial or non-financial interests to disclose.

Availability of data and materials

The datasets generated and/or analyzed during the current study are available in the repository (Rodrigues and Garcés, 2026).

Ethics approval and consent to participate

The study was performed following the Declaration of Helsinki, and the protocol was approved by the Ethics and Research Committee of the State University of Paraíba (approval number: 34702520.2.0000. 5187).

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