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

Eujessika Rodrigues (✉ eujessikars@gmail.com)  
Federal University of Rio Grande do Norte – UFRN

Paulo Barbosa  
Center for Strategic Health Technologies – NUTES

Daniella Carvalho  
Center for Strategic Health Technologies – NUTES

Elisa Nakagawa  
University of São Paulo – USP

Sabrina Fernandes  
Federal University of Rio Grande do Norte – UFRN

Ana Tereza Fernandes  
Center for Strategic Health Technologies – NUTES

Lina Garcés  
Federal University of Itajubá

Álvaro Maciel  
Federal University of Rio Grande do Norte – UFRN

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Abstract

Background: the increasing number of older adults and the inherent disabilities of human aging have been one of the biggest challenges in the health field. Hence, health technologies have been widely explored to improve the quality of life of older adults. In particular, technologies based on heart rate variability (HRV), which measures the decrease of vagal tone and sedentary behaviours in age, could be remotely used in older adults’ care. In turn, this measure has been only made available for clinical testing environments, laboratories, and hospitals. This paper presents a platform named SMH (Senior Mobile Health), which supports the development of a complete system composed of mobile apps deployed in wearables as well as 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 platform and validated the results by comparing them with those provided by a reference clinical tool, the Kubios HRV.

Conclusions: we conclude the SMH platform can aggregate an important value to older adults’ care assisting in rehabilitation processes by health professionals.

Introduction

According to the United Nations, there were about 982,271 million older adults in the world in 2017; by 2030, this number will rise to approximately 1.6 billion [1]. The increasing number of older adults has become one of the biggest challenges in the health field, affecting countries all around the world. As the population aging grows and, concomitantly, the diseases and disabilities present in this aging process, the health area has suffered continuous changes, and advances are necessary to promote better services to this population [2] [3].

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 elderlies [4]. Examples of these technologies are presented in [5], [6], [7]. 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 analyse the heart rate variability (HRV). The HRV has been an object of study for several years and can indicate the decrease of vagal tone due to human aging and sedentary behaviours [8]. Means to monitor HRV are required to provide a better quality of life for older adults. However, the technologies above mentioned are not suitable for remote monitoring scenarios like in the current pandemic. These technologies are only suitable to be used in clinics, hospitals, and test environments [9]; in other words, the value of remotely measuring and analysing the HRV data of the older adult has been left aside.

This paper introduces SMH (Senior Mobile Health), a platform based on microservices and the Internet of Things (IoT) focused on HRV for remote health monitoring of older adults. We present the SMH architecture and its main features and discuss the challenges to collecting and treating HRV data from wearable devices. We also present a real-world case study involving 89 older adults to evaluate the
feasibility and performance of our platform to calculate and predict HRV, i.e., three cardiac modulation indices in the time domain.

This paper is organized as follows. The second section details the SMH platform. The third section presents the case study for validating of the HRV features. The fourth section discusses the main findings of this work. Finally, the fifth section draws the conclusions.

Method

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 platform. This section also illustrates its main user interfaces.

Main Features and Context

The main users of the SMH platform are health professionals (e.g., geriatrics and physiotherapists) and caregivers that provide health monitoring services for elderlies. 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 heart rate (HR) besides other health indicators, medicines, frailty analysis, daily progress, gait speed, and risk of falling [10].

Using sensors, such as accelerometers and photoplethysmography, to analyse the movements and steps during the nights, the SMH platform can identify how often the individual wakes up at night and goes to the bathroom, for example. With this information, health professionals can guide elderlies 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 period of sleep. This condition is recurrent in elderlies due to factors inherent in the aging process [11].

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 [12].

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 widely used by health professionals [13] [14]. However, the measure of gait speed is sometimes collected manually by health professionals and then calculated. The SMH platform 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 is 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 elderlies. For that, SMH encompasses machine learning algorithms to predict adverse health outcomes and promote real-time and continuous monitoring of the users.

**Software Architecture**

The software architecture of the SMH platform is based on microservices and IoT and reuses our previous experiences with the implementation of healthcare services [15] and an IoT-based architecture [16]. Figure 1 shows the SMH architecture composed of nine core components:

- **Express Gateway**: It is the API Gateway, 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's information;
- **MHealth (Measurement of Health data)**: Microservice in charge of storing measurements of HRV, weight, blood pressure, physical activity, sleep, among others;
- **Notification**: Microservice responsible for sending e-mails and SMS and pushing messages using Firebase Cloud Message for web system and mobile devices;
- **DS Agent (Data Synchronization Agent)**: Service in charge of external data synchronization (from wearable devices) with the SMH platform. A synchronization implies the user data capture in the external service, the pre-processing of data to convert it into the data model supported by the SMH platform, 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 own 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 platform.

In short, on top of Fig. 1, 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 (smart phones) and wearable devices (smart watches and smart bands Fitbit and other brands) are responsible for collecting older adults’ data and providing support to caregivers in the health status and engagement. 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.

**HRV Calculation**

The HRV reflects the oscillations in the interval (in millisecond) 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 from cognitive impairment in the elderly population [17] [18] [9].

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 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 heart beats 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 2 presents the main steps of our HRV calculation. In Step 1, the data acquired from Fitbit that consists of the heart rate 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 a greater accuracy, ensuring that the data would be filled in a satisfactory way [19]. Hence, we selected and implemented the PCHIP (Piecewise cubic Hermite interpolating polynomial) method, which presented a RMSE of 1.14 [20].

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) [20] that seek to approximate the data obtained from wearable devices to the data coming from ECG sensors, where given a dataset composed of IPI (inter-pulse intervals) as inputs and the IBI (inter-beat interval) as outputs, 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, is calculated using the following equation [19]: \(HR = \frac{60000}{IBI}\).

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 detecting of 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 [20].

In particular, to remove the inconsistencies described in Step 4, we compared four different methods provided by the hrv-analysis library, distributed under the GPLv3 license, 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 method adopted for our work was the Kamath Rule [21] since it provided the most similar results to Kubios (the tool used as 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 patients’ 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 [22].

**User Interface of SMH**

Figure 3 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 elderly can manually insert. In particular, this screen shows questions about fatigue that can help calculate the frailty indicators of elderly.

Figure 4 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 Fig. 4 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 5 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.

**Results**

We conducted a real-world case study using the SMH platform and addressed the following research question (RQ): *Can the SMH platform provide reliable HRV metrics?*

The team of researchers that conducted this case study involved health professionals and data analysts.

The sample of this research consisted of 89 community-dwelling individuals aged 60 years or older, 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 Paraíba (approval number: 34702520.2.0000. 5187) and was performed in accordance with 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 out from May 2020 to June 2022. During this period, the time series was saved on the SMH platform.

Figure 6 illustrates the design of our case study. We evolved the results presented in [22] with a more significant number of older persons with data already stored in the SMH platform. In short, in (1), we extracted the data of 89 older persons satisfying the criteria of having a 15 minutes timeseries with no activity and no steps registered, the elderly at rest. This simulated the previous experiment in [22], where we collected data of older persons using Polar H10 chest straps in the resting state. Now the goal is to show the effectiveness of the SMH platform when conducting such HRV experiments without the chest strap device. After that, in (2), the SMH platform 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 widely 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.

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 7, 8, and 9 compare the SDNN, RMSSD, and pNN50, respectively, calculated by Kubios and SMH.

Additionally, as we want to compare HRV metrics using the same paired observations on a single group of participants, we performed a paired Student's t-test (Table 1) to determine whether the paired observations are significantly different from other. Using the significance level of 0.01, the confidence level of 99%, and 88 degrees of freedom (n-1), the critical value of t obtained from the t distribution table is 2.369.

The t statistic for the SDNN was 1.251, which was smaller than the critical value of 2.369. The p-value was 0.214, 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 t statistic was −0.611, which was also smaller than the critical value. The p-value was 0.543, which was greater than the significance level, so we accepted the null hypothesis that there is no difference between the means. For pNN50, the obtained t statistic was 0.724, which was also smaller than the critical value. The p-value was 0.471, which was 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 platform and Kubios.
To evaluate the HRV metrics resulting from the SMH platform 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 [23]. 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 HRV metrics are traditionally measured in hospitals, clinics, and laboratories using ECG equipment or Holter monitor. These devices require expert setup, therefore, widely 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 the older adults’ health, early risk identification in their patients, and better conditions to follow the care for them.

**Discussions**

By delivering the SMH platform, we have received excellent feedback from health professionals and patients concerning improving in 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 in this period.

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 of 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 elderlies’ health, 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 platform 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 heart rate measurements provided by Fitbit devices, as, we usually have only one measurement for every 5 seconds. The process of filling this data was presented in [20], and it was challenging in this work, where this constraint did not impact the overall results of HRV.

**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 people. This paper contributes with a health technology that supports the remote monitoring of the elderlies’ health. The main take-away message of this work is that the calculation of HRV rates from elderlies’ 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 platform 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 elderlies is observed. Due to their value, we claim health technologies should be more investigated, delivered, and widely adopted to contribute to healthy aging increasingly.
Declarations

Ethics approval and consent to participate:

The study was performed in accordance with the Declaration of Helsinki and protocol was approved by the Ethics and Research Committee of the State University of Paraiba (approval number: 34702520.2.0000. 5187).

Consent for publication:

Not applicable.

Availability of data and materials:

The datasets generated and/or analyzed during the current study are available in the repository: https://drive.google.com/file/d/1QEJ1D15AVDkLpBpkN9CFgbChphDyw9g/view?usp=sharing. And are available from the corresponding author on reasonable request clicking on the link.

Competing interests:

The authors declare that they have no competing interests.

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Author contributions:

Rodrigues; Barbosa and Maciel conceived of the presented idea. Rodrigues; Fernandes and Fernandes designed and performed the experiments. Carvalho; Nakawaga 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.

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References


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Software architecture of SMH platform.
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Figure 4
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Figure 7

Standard deviation of all normal RR intervals (SDNN) for Kubios and SMH.

Figure 8

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Figure 9

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