Deliverable Number

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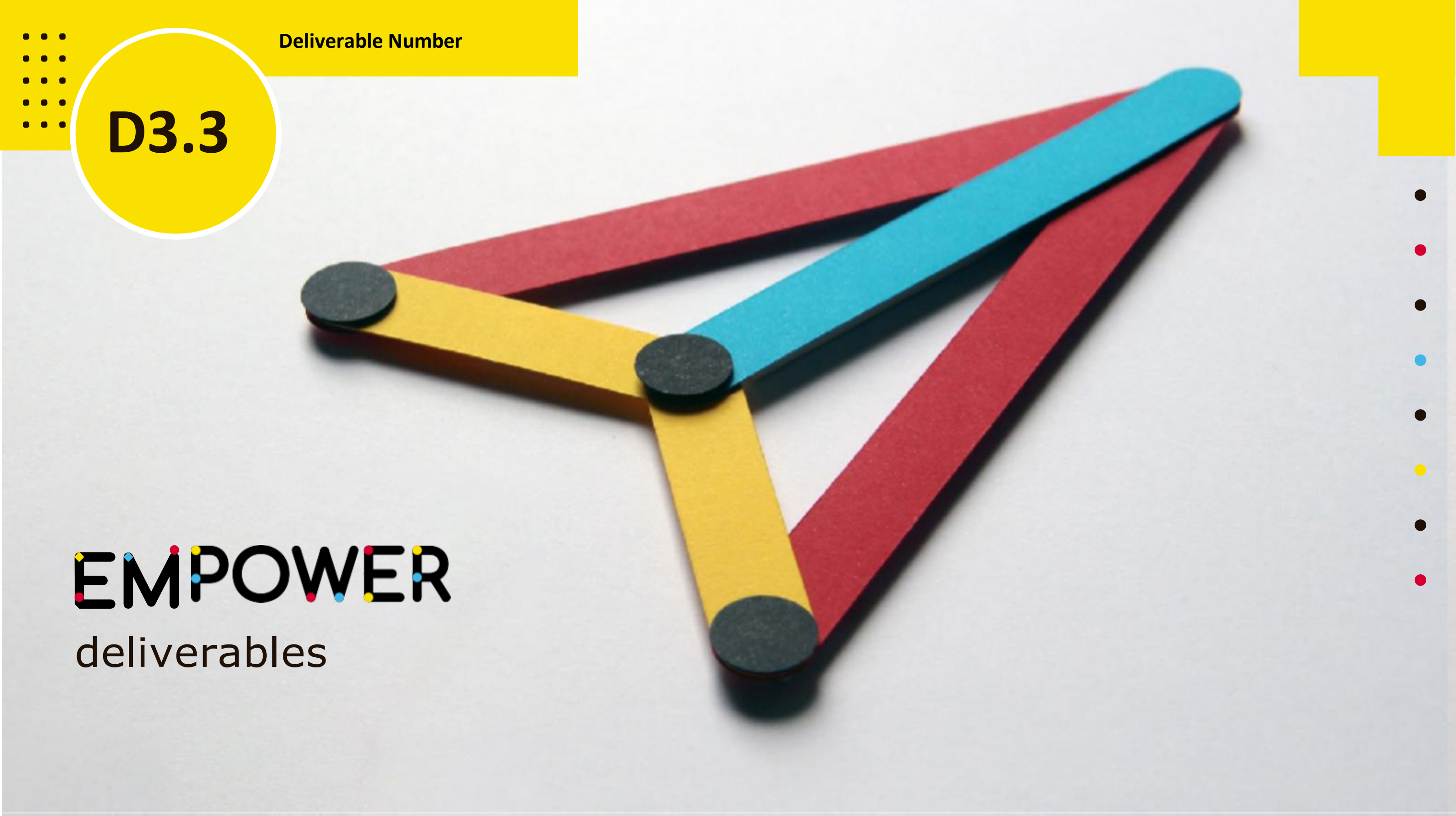

EMPOWER

deliverables

Deliverable name	**WEARABLES MODULE**
Type	**DEM — Demonstrator, pilot, prototype**
Dissemination level	**PU - Public**
Date	**Month 12**

This deliverable provides detailed information on the implementation of the Wearables module.

Description

WP.3

Work Package. 3

Lead Beneficiary – (UV)

IRTIC

Universitat de València

Wearables Module

The wearables module is concerned with recording **heart rate, RR interval (the interval between two successive heartbeats),** and **accelerometer** data while the children interact with the Empower Platform games. We aim to use "off the shelf" devices that stakeholders can easily procure. This will ensure the platform can be easily adapted and integrated into existing educational settings with minimum financial and technical configuration effort.

This document will also briefly overview the first pilot testing outcomes and analyse statistical information on the recorded data. The main challenges will be highlighted, and remedial actions will be proposed.

Date	Version	Description	Authors
12.09.2023	0.1	First draft of the deliverable	Victor Bâcu Constantin Nandra Raul Gorgan
18.09.2023	0.2	Second draft of the deliverable	Adrian Sabou Teodor Ștefănuț
26.09.2023	0.3	Release candidate – alpha version	Teodor Ștefănuț

Table of Content

#1. Introduction

Wearables have become a standard accessory for many people, relying on them to glimpse their health, resting habits, and sports performance. Along with the technical progress, these devices are becoming more advanced, with better sensors and algorithms to record, process and interpret the data. Although, at this time, the data readings provided by these devices are not research grade, they are still reliable and relevant as statistical information.

Striving to keep a low price for the devices themselves, most of the owning companies are monetising recorded data from the users in different ways. The most common is storing all the data in their private cloud and allowing third parties access to other statistics and anonymised data through paid APIs. This approach also adds a variable amount of delay to accessing information, which, in our case, was an important aspect to consider.

EMPOWER aims to develop and provide stakeholders with a platform that can be integrated into existing educational settings with minimum financial and technical configuration effort. To achieve this, we have identified “off the shelf” devices which provide access to raw data recorded by the sensors and allow real-time access to the values. This access is not conditioned on any fee, once or annually, and does not require storing information on infrastructure outside the EMPOWER platform.

In the following sections, we have briefly presented the analysis performed on the candidate devices and the reasons behind selecting a specific device for development and pilot studies. We will also highlight the main challenges discovered in the first pilot and describe the remedial actions taken or planned to be implemented. Finally, a statistical summary of the data recorded in the first pilot has been included.

#2. Available devices overview

The relevant characteristics of the available wearable devices we have been considering for this project were real-time access to raw sensor data, the possibility of accessing said data through dedicated APIs, and whether the data access was free. The table below briefly overviews the most well-known wearable devices available when writing this report.

Filtering by free data availability and existing, documented APIs, out of the above, we decided to do a more in-depth dive into three leading platforms: WearOS (based on Android), WatchOS (Apple) and Fitbit.

Table 1. Comparison of Smart Watch devices

Producer	Top Devices	Real-Time Data Access	Free Data Access	Available Raw Data	API
Samsung	Galaxy Watch 5, 4	✓	✓	Yes, multiple sensors	Samsung Health API
Apple	Apple Watch Series 8, 7	✗	✓	Yes, for some sensors. Limited, filtered access.	Apple HealthKit API
Garmin	Fenix 7 Epix	✓	✗	Yes, multiple sensors - paid subscription	Garmin Connect API
Mio	Mio Alpha 3 HR Mio Alpha 2 HR	✓	✗	3rd party apps	MIO Development Kit
Fitbit	Fitbit Sense Fitbit Versa 4	✗	✓	Yes, via Web API	Fitbit Web API
Xiaomi	Mi Watch S1 Mi Watch S1 Active	✗	✗	Not officially, 3rd party apps	Xiaomi Open API

WATCHOS

This is the Apple ecosystem and, therefore is limited in the range of available devices, the top products now being the latest models: Apple Watch 7 and 8.

Apple's wearable devices do not provide direct access to raw data. Still, developers can access a subset of data, such as heart rate, steps, distance travelled, and sleep data, through the HealthKit framework.

- Available sensors: electrical cardiac sensor, optical cardiac sensor, blood oxygen sensor, altimeter, compass, high dynamic range gyroscope, ambient light sensor
- Relevant obtainable data: blood oxygen levels, ECG, heart rate, body temperature
- Available programming languages/ APIs: Swift, Objective-C through Apple HealthKit API
- Advantages:
    - Strong support from Apple; well-documented API
    - High-quality third-party apps
- Disadvantages:
    - Only available on Apple devices
    - High prices - with Apple Watch 8 starting from $400
    - Restricted access to raw sensor data

WEAROS

In this ecosystem, we find products from a variety of vendors. This provides more choices, often at more accessible prices. One possible drawback would be the lower levels of consistency in terms of capabilities and user experience.

Samsung Galaxy Watch

- Available sensors: bioelectrical impedance analysis sensor, electrical heart sensor, optical heart rate sensor, accelerometer, barometer, compass, gyroscope, light sensor, temperature sensor
- Relevant obtainable data: blood oxygen levels, ECG, heart rate, skin temperature
- Available programming languages/ APIs: Java, Kotlin through Tizen SDK
- Advantages
    - Lower prices - with Galaxy Watch 5 starting from $300
    - Support for third-party applications
    - Access to raw sensor data
- Disadvantages
    - Less mature platform than WatchOS - with support from Google still being added.

Mobvoi TicWatch Pro 3 Ultra

- Available sensors: accelerometer, gyroscope, barometer, SPO2 sensor, heart rate monitor, ambient light sensor, low latency off-body sensor
- Accelerometer, Gyro Sensor, HD PPG Heart Rate Sensor, SpO2 Sensor, Low Latency Off-Body Sensor, Barometer
- Relevant obtainable data: blood oxygen levels, heart rate
- Available programming languages/ APIs: Java, Kotlin
- Advantages
    - Lower prices - starting from $205
- Disadvantages
    - No ECG data
    - isn't running the latest wear OS

Fossil Gen6

- Available sensors: PPG Heart Rate, SPO2, Accelerometer, Altimeter, Ambient Light, Compass, Gyroscope, Off-body IR
- Relevant obtainable data: blood oxygen levels, heart rate
- Available programming languages/ APIs: Java, Kotlin

- Advantages
    - Lower prices - starting from $200
- Disadvantages
    - Fewer sensors when compared to Samsung and Google models
    - isn't running the latest wear OS

Google Pixel Watch

- Available sensors: Blood oxygen sensor, Multipurpose electrical sensor, Optical heart rate sensor, Accelerometer, Compass, Altimeter, Gyroscope, Ambient light sensor
- Relevant obtainable data: blood oxygen levels, heart rate, ECG, skin temperature
- Available programming languages/ APIs: Java, Kotlin
- Advantages
    - Lower prices that WatchOS - starting from $300
    - Access to raw sensor data
- Disadvantages
    - Not available in the acquisition stage of our project

FITBIT

- Available device: Fitbit Versa 4
- Available sensors: blood oxygen sensor, heart rate sensor, accelerometer, altimeter, ambient light sensor
- Relevant obtainable data: blood oxygen levels, heart rate, skin temperature
- Available programming languages/ APIs: JavaScript, through Fitbit SDK
- Advantages
    - Lower prices - starting from $200
    - Better battery life

- Disadvantages
  - Difficulties in accessing real-time data
  - Fewer sensors and, overall, less capable hardware

#3. Wearables integration in EMPOWER platform

Based on the analysis presented in section #2, we have selected Samsung Galaxy Watch 5 as a development, testing and pilot device for the EMPOWER platform. Compared to the other devices, it packs more and better-quality sensors. It also provides WearOS as an operating system, which allows us to develop an initial software solution that can be easily adapted to a few other providers, extending the impact and the audience of the EMPOWER platform.

Access to the data recorded by the heart monitoring sensors is allowed only through a Privileged SDK that is provided by Samsung free of charge upon a written request. As sensor readings vary from 1Hz to 300Hz, the values are cached on the device for 1 second and then sent in batch to the EMPOWER server over a secured HTTPS connection.

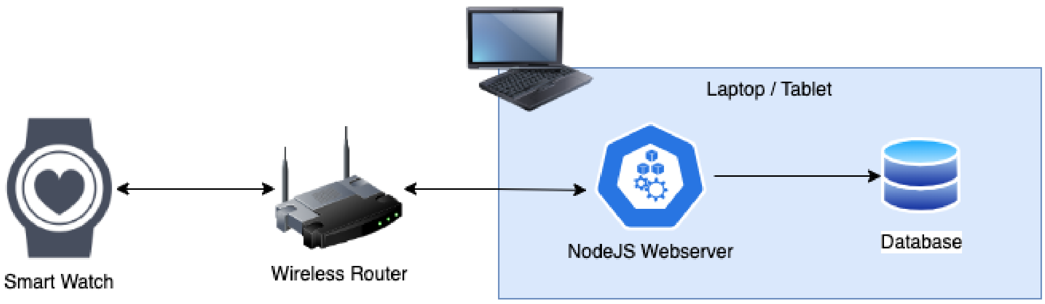

Figure 1. General view of the Wearable integration

The data from the wearables is saved in the database with direct connections to the (1) working session, (2) performed activity, and (3) timestamp correlations. This facilitates post-processing actions focused on specific activities and allows granular selection of the records.

#4. Sensors usage limitations in EMPOWER

Available sensors: Accelerometer, Barometer, Bioelectrical Impedance Analysis Sensor, Electrical Heart Sensor, Gyro Sensor, Geomagnetic Sensor, Light Sensor, Optical Heart Rate Sensor

ELECTRICAL HEART SENSOR

An Electrocardiogram, commonly called an ECG or EKG, represents a documentation of the heart's electrical activity. The ECG can be measured using the Electrical Heart Sensor available on Samsung watches. To ensure accurate measurement:

- Before taking the measurement, it is essential to remain seated in a stable position on a chair with back support for at least 5 minutes without any movement or conversation.
- Keep your feet flat on the floor, avoiding crossing your legs during the measurement.
- Maintain a consistent wrist position while the measurement is ongoing.
- Refrain from speaking, yawning, or making unnecessary movements during measurement.
- Place the forearms on the table and lightly touch the top button for 30 seconds (see Figure 2)

All these conditions make it hard to integrate the readings from this sensor in our project. We aim to record data while the children do other activities (e.g., playing games and answering questions). At the same time, most of the requirements above are difficult to implement by a child with NDD.

Figure 2. Example of how to measure ECG[1]

BLOOD OXYGEN SENSOR

Utilising the Samsung Galaxy Watch to measure blood oxygen levels (SpO2) can be valuable, particularly when engaging in physical activities or monitoring one's general well-being. Nevertheless, it's essential to be aware of certain factors and constraints. For an accurate measurement, it is advisable to position your hand on a stable surface close to your heart and refrain from making any movements or engaging in conversation during the measurement process (see Figure 3).

Figure 3. Example of how to measure oxygen level in the blood[2]

These requirements are also too restrictive for our purpose and difficult to implement by our target users.

OPTICAL HEART RATE SENSOR

The Optical Heart Rate Sensor found in Samsung watches is a crucial component engineered for precisely measuring heart rate. To initiate the process, it is imperative to securely wear the Samsung watch on your wrist, ensuring a snug fit for accurate heart rate readings.

This sophisticated sensor employs a combination of green and infrared LED lights, penetrating your skin and the blood vessels on your wrist. As the light travels through, the sensor discerns fluctuations in light absorption attributed to blood flow. Consequently, the sensor gathers data from the reflected light, effectively quantifying alterations in blood volume corresponding to your heartbeat. Subsequently, this data undergoes processing through the watch's internal algorithms.

[1] Source: https://www.samsung.com/ro/apps/samsung-health-monitor/
[1] Source: https://www.samsung.com/au/support/mobile-devices/measure-blood-oxygen-levels/

Samsung's Optical Heart Rate Sensor is designed to provide dependable heart rate measurements across diverse circumstances. Adhering to the recommended method of wearing the watch will guarantee the precision of these readings.

Figure 4. Example of the measured value with an optical sensor. No explicit user interaction is required.[3]

As this sensor can be continuous, made in parallel with other activities, and does not require any specific pose or action from the user, we have focused on these readings for monitoring heart activity.

BIOELECTRICAL IMPEDANCE ANALYSIS SENSOR

The Bioelectrical Impedance Analysis (BIA) sensor enables precise measurement of your body composition, providing insights into factors like body fat percentage, body water content,

[3] Source: https://www.samsung.com/ca/support/mobile-devices/samsung-smartwatch-heart-rate/

and skeletal muscle mass. This process involves the transmission of small electrical currents through the body to assess the quantities of muscle, fat, and water. To ensure accurate measurement:

- Position your arms at chest level, ensuring that your armpits are not in contact with your torso.

- Maintain your fingers on the Home and Back buttons, avoiding contact with other areas of your watch throughout the measurement.
- Avoid any movement during the measurement process.

Figure 5. Measuring bioelectrical impedance[4]

#5. HRV computation methods and interpretation

Heart Rate Variability is a quantitative measure that assesses the variation in time intervals between successive heartbeats. It serves as a valuable indicator of the changes in the Autonomic Nervous System. It is measured milliseconds and can be derived from electrocardiogram (ECG) or photoplethysmography (PPG) data.

HRV computing and interpreting has become an essential technique in health monitoring, stress assessment and reaction to stimuli. It reflects the influence of the autonomic nervous system on heart rate. The autonomic nervous system comprises two main components: the sympathetic and parasympathetic systems, and HRV indicates the balance between these two. The sympathetic nervous system is responsible for the “fight or flight” response, increases the heart rate and decreases HRV. In contrast, the parasympathetic nervous system is responsible for the “rest” response, slows heart rate and increases HRV. Previous studies regarding this parameter identified that a high value of HRV represents a healthy state and a low level of stress or anxiety. A low value

[4] Source: https://www.samsung.com/latin_en/support/mobile-devices/measure-your-body-composition-with-the-galaxy-watch-series/

of HRV indicates problems in reactions and body adaptability in the environment induced by stress, anxiety or other health risks of cardiovascular diseases.

Because of the sensor usage limitations described above, PPG data can be used to compute HRV. Photoplethysmography is a non-intrusive technology that uses infrared light to measure the variations in blood volume. It consists of a light-emitting diode and a photodetector, as illustrated in Figure 6. The diode emits light, and the photodetector measures the quantity of light reflected. This quantity indicates the blood volume variations from the vessels during a heartbeat.

The absorption is different at the moment of a heartbeat, so it can be identified. This technology provides several parameters that can be used to collect information about human reactions and behaviour based on heart activity: heart rate, the interval between two successive heartbeats (RR interval), the arterial stiffness, the systolic amplitude, or the pulse area. The RR interval offers more valuable insights in heart activity and will be used to compute HRV. There are several methods to compute HRV; the most important will be described later.

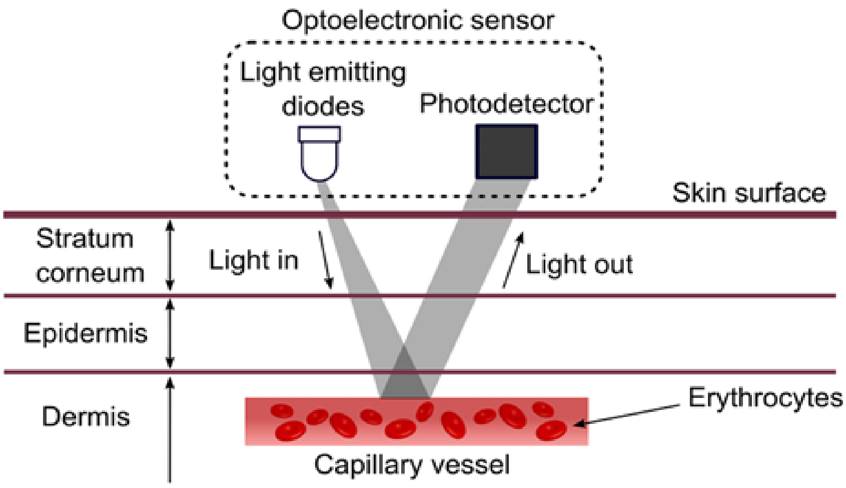

Figure 6. Photoplethysmography working principle[5]

REQUIREMENTS

To conduct HRV analysis effectively and to have an accurate result, there are some requirements that must be met:

Hardware Requirements: A device that contains reliable heart rate monitoring equipment, such as PPG sensors is necessary for data collection.

[5] Source: https://www.mdpi.com/1424-8220/18/6/1894

Software Requirements: A library that provides direct access to raw data from sensors (e.g. for Samsung smartwatches with WearOS: Samsung Privileged Health SDK) and software capable of processing and deriving HRV value from the data.

Data Quality: High-quality data with minimal noise and artifacts is needed for accurate HRV analysis.

Data Duration: The duration of data collection should be sufficient to capture meaningful HRV patterns, typically at least 2 minutes.

COMPUTATION METHODS

Before HRV analysis, data pre-processing is essential. This includes noise removal, artefact correction and segmentation to ensure data quality. PPG signals provide data such as heart rate, heart rate status, IBI (the interval between two successive heartbeats) and the qIBI (quality of IBI) with the frequency of 1Hz. QIBI is used to ensure the quality of data arrived and based on it; a value is used or not for HRV computing. Once the data is prepared, a variety of computation methods are employed to extract HRV.

HRV is computed using the RR interval, and there are several methods and equations based on context and type of research. The more common are the time-domain and frequency-domain methods but some methods use non-linear metrics, spectral analysis, and time-frequency analysis.

In the time domain, the analysis consists of the quantity of time between the heartbeats and results in an absolute value. This value can be compared with other values collected at different moment to identify the variations and make decisions based on them. The heart signal is passed through a Fourier transformation in the frequency domain, and the lower and higher frequencies can be distinguished. The lower frequencies represent the influence of the sympathetic nervous system, and the higher frequencies represent the influence of the parasympathetic nervous system. In frequency-domain measurements, there is a higher latency due to computation complexity.

The main methods of computation used in time domain are: Mean RR (Mean Value of the RR intervals), SDNN (Standard Deviation of the NN/RR Intervals), SDSD (Standard Deviation of Differences between Successive RR Intervals) and RMSSD (Root Mean Square of Successive Differences). Other time-domain methods are NN50 (Number of interval differences of successive NN intervals more significant than 50 ms) and pNN50 (Percentage of NN50 divided by the total number of NN intervals).

Mean RR represents the mean value of the RR intervals, presented in Equation 1. This does not offer valuable information about heart activity, but it can be used to measure SDNN. RRn represents the RR value of the nth interval.

$$\overline{RR} = \frac{1}{N}\sum_{n=1}^{N} RR_n$$

Equation 1. Mean RR

SDNN stands for the standard deviation of the NN/RR intervals, presented in Equation 2. This method has the disadvantage that it requires the calculation of two values for each measurement, the Mean RR and the final SDNN.

It passes through all the data twice and this can introduce latency and problems in synchronicity.

$$SDNN = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}(RR_n - \overline{RR})^2}$$

Equation 2. SDNN formula

SDSD represents the standard deviation of differences between successive RR intervals, and it is presented in Equation 3. This method can be used to measure the variations over a very short time interval. Therefore, a different method should be used, as there is a need for a longer period for analysis.

$$SDSD = \sqrt{E\{\Delta RR_n^2\} - E\{\Delta RR_n\}^2}$$

Equation 3. SDSD formula

RMSSD represents the root mean square of the successive differences between heartbeats and can be used to measure the absolute value of the heartbeat variations. This equation has the advantage that any number of intervals between consecutive heartbeats can be used and addresses the short-length analysis behaviour and complexity of other methods. The formula of RMSSD is presented in Equation 4:

$$RMSSD = \sqrt{\frac{1}{N-1}\sum_{n=1}^{N}(RR_{n+1} - RR_n)^2}$$

Equation 4. RMSSD formula

Frequency-domain analysis involves transforming HRV data into frequency components using techniques like Fourier Transform. Key metrics include LF (Low-Frequency power), HF (High-

Frequency power), and the LF/HF ratio, which reflects the balance between sympathetic and parasympathetic activity.

Nonlinear HRV metrics, such as SD1 and SD2 (Poincaré plot parameters) and ApEn (Approximate Entropy), provide insights into the complexity and adaptability of the heart rate signal but require very complex calculations, instability, and unreliability. Other methods that are not widely used are spectral analysis and time-frequency analysis. Spectral analysis decomposes HRV data into frequency components, allowing for a more detailed examination of autonomic nervous system activity. Time-frequency analysis methods, such as wavelet transform, provide a dynamic view of HRV across time and frequency domains. These two are not used because they are hard to use, complex and can introduce errors and latency.

RMSSD is used to collect the absolute value of the heart rate variability based on an arbitrary amount of data, as this offers stability and accuracy. After data collection and HRV computing, the values are analysed and interpreted.

INTERPRETATION

The interpretation of the data is essential to have good system accuracy. Without history about the user and information about age, gender, actual health or other relevant parameters, the proposed solution uses a base value of HRV collected before the actual measurement starts. This value is considered a “ground truth” and serves as a measurement reference. The sensors need a short period of approximately 2 minutes to stabilise the data, and the connection is set when this period expires. When the height starts, the new values of HRV are stored, analysed, and interpreted. The general overview of the system’s working principle is presented in Figure 3.

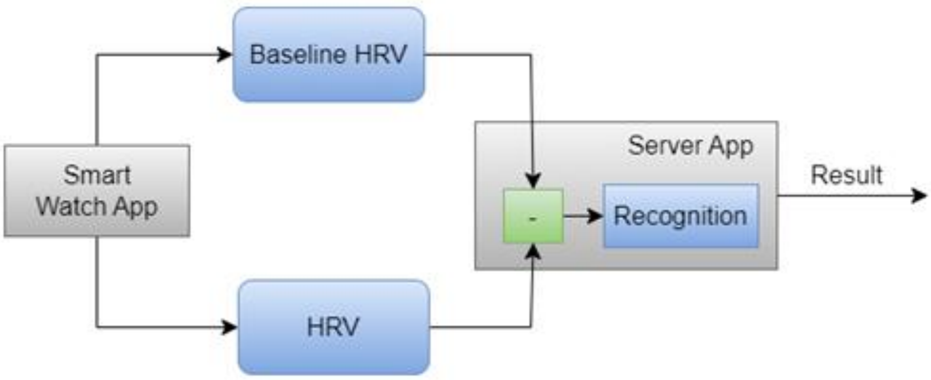

Figure 7. General overview of the recognition steps

The system's performance is influenced by the number of IBI values considered when computing HRV. A window of 120 valid IBI values is considered sufficient because the changes are accurately identified, and patterns can be extracted. Because of noise, qIBI recalls some data as wrong, and there is a need for more than 2 minutes for 120 correct values even if the frequency of collection is 1Hz.

The reference HRV value is used to compare the subject's behaviour and reaction regarding the start of the measurement. If the value of HRV is lower than the reference, the issue passes through states of stress and anxiety or indicates other problems.

Heart Rate Variability (HRV) is a valuable parameter with applications that extend beyond cardiovascular health into areas such as stress assessment or behaviour and reaction to stimuli analysis. Understanding the dynamics of HRV, its measurement techniques and clinical significance, subjects' behaviour can be analysed in detail, and accurate decisions can be made.

#6. First pilot data analysis

First pilot data was collected during the pilot sessions held in Romania and Portugal. Anonymised data was gathered from a total of 13 participants from Romania and 11 participants from Portugal.

The most critical data analysed are as follows: the total duration each participant spent in each activity, the total number of heart rate values recorded per activity, the total number of valid heart rate values per activity, the total number of IBI values per activity and the total number of good IBI values per activity. Additionally, the number of valid heart rate values per second and proper IBI values per second were computed. While heart rate-related values were directly obtained from the wearable device, durations were computed based on the database's start and end timestamp of each recorded activity.

Table 2. Summary of wearable data recorded in the first pilot

Pilot data collected	Romania	Portugal
Total HR values	41631	6138
Total Valid HR values	33742	3366
Total IBI values	41631	6138
Total Valid IBI values	30500	4412
% valid HR values	81,05	54,84

% valid IBI values	73,26	71,88
Average time (s) between valid HR values	0,93	4,00
Average time (s) between valid IBI values	2,18	6,27

Table 2 summarises the wearable data collected in the first pilot study. Data collection from Romania has been performed with the debug version of the application, while the release version has been used in Portugal. This has determined a significant difference in the number of recorded values and made us aware of the issue, which has already been fixed.

Another important thing to highlight from the above summary is the percentage of the valid values from the recorded values. The low ratio indicates that the watch's positioning on the children's hands needs to be improved. We are currently focusing on two main directions: (1) how high the device should be placed on the forearm, and (2) how to improve the resilience of data recording while sudden moves happen.

WEARABLE DATA IN MARIADB DATABASE

The wearable sensor provides heart related data once each second. Each reading is added as a separate row into MariaDB dedicated table, that has the following columns (please see figure below):

- **value_heart_rate** – the value of the current heart rate expressed in beats / minute
- **status_heart_rate** – provides quality information about the recorded heart rate value. Possible values are:
  - **10** – heart rate value is valid
  - **111** – heart rate value is invalid (wearable detached or signal weak)
  - **113** - heart rate sensor is initializing
- **value_ibi** – the duration of the last in-between-interval recorded by the sensor, expressed in milliseconds
- **status_ibi** - provides quality information about the recorded IBI value. Possible values are:
  - **11** – IBI value is valid
  - **109** – IBI value is missing (the sensor could not compute the value)
  - **110** – IBI value is invalid (signal weak)
- **id_activity** – the ID of the game activity performed by the student at recording time, represented as a FOREIGN_KEY value to the **activity** table
- **id_session** – the ID of the game session active at recording time, represented as a FOREIGN_KEY value to the **session** table

- **timestamp** – the millisecond when the value has been recorded by the sensor, expressed as the number of milliseconds since Unix Epoch (1 January 1970 00:00:00 UT)

id ▲ 1	value_heart_rate	status_heart_rate	value_ibi	status_ibi	id_activity	id_session	timestamp
251	113	10	483	11	1	1	1684744473858
252	113	10	526	11	1	1	1684744474858
253	113	10	531	11	1	1	1684744475858
254	113	10	537	11	1	1	1684744476858
255	113	10	530	11	1	1	1684744477858
256	114	10	539	11	1	1	1684744478858
257	113	10	540	11	1	1	1684744479858
258	114	10	576	11	1	1	1684744480858
259	114	10	971	11	1	1	1684744481858
260	113	10	549	11	1	1	1684744482858
261	113	10	576	11	1	1	1684744483858
262	112	10	568	11	1	1	1684744484858
263	111	10	552	11	1	1	1684744485858
264	111	10	531	11	1	1	1684744486858
265	111	10	535	11	1	1	1684744487858

Figure 8. Example of wearable data stored in MariaDB for the first EMPOWER Pilot

WEARABLE DATA ANALYSIS

As can be seen from the previous section, the data structure allows us to identify all the records registered by the wearable sensors while the students have performed different activities or they have answered the questionnaires (in between activities).

Our first step in processing recorded data has been focused on computing the HRV for each activity type, using RMSSD. Also, we had one value computed for all the time intervals between the activities, that we have intended to use as a baseline in our analysis. The second step of the analysis has been steered towards identifying different levels of stress or even basic emotions (e.g. happiness, frustration) connected with the stimuli represented by the games played by the students.

The results obtained analysing only the data from the first pilot have been limited, as initially foreseen. Due to the small quantity of data available for algorithms training it is not yet possible to accurately identify specific trends or relevant characteristics. Also, given our research specificity (children with NDD, 6-12 years old) it has not been possible to augment our training set with other datasets available in the literature. In the second pilot we will record twice more data than we have recorded in Pilot 1.

#7. Access to source code and compiled packages

The WearOS application implemented to gather wearables data can be downloaded in source code or compiled format. Everything is accessible on GitHub from the private repository: https://github.com/cgis-empower/client-wearos/tree/galaxy-watch.

In this repository, one can find

- configuration tutorials – how the watch needs to be configured before & after application installation – in PDF and video formats
- compiled APK file – requires a Samsung Galaxy Watch and a more advanced setup to be installed
- source code – requires Android Studio, a Samsung Galaxy Watch and proficiency in Android mobile development to be installed

#8. Conclusion

Currently, many intelligent, wearable devices can be used “off the shelf” to monitor physiological data while performing different activities: sports, regular work activities, sleeping, etc. However, very few of these allow third-party programmers to access this information at a low level (as close to the hardware sensors as possible).

As one of our primary goals is to identify solutions that can be implemented in existing educational settings with minimum financial and technical setup effort, we have identified the most promising devices that allow free access to sensors and made a comparison from their sensor’s capabilities perspective. As a result of the analysis, Samsung Galaxy Watch 5 has been selected.

The first pilot testing performed has highlighted a few challenges that need to be addressed:

- the size of the watch, compared to children’s wrist size, creates positioning issues
- there are subtle differences in behaviour between **debug** and **release** versions of the application

At the same time, the pilot testing has demonstrated that the proposed solution provides a scalable and stable connection between the watch and the server, allowing the transfer in almost real-time (once a second) of all the recorded parameters.