An Intelligent Ecosystem for Improving Brain Disease Monitoring of Patients Using Wearable Devices and Artificial Intelligence

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***Abstract*—Nowadays, neurological diseases represent a medical emergency for which new prevention, monitoring and adequate treatment solutions are needed. ALAMEDA project proposes a monitoring solution for patients with Parkinson's disease, Multiple Sclerosis, and Stroke, using multiple sensors and specific applications to collect information on the condition of health and aspects of lifestyle, activity level, sociability and mood. The paper describes the ALAMEDA infrastructure architecture and all processes to support the dedicated AI toolkit, along with all relevant concepts, components and interactions. Data collection methods are central to the objectives of the ALAMEDA project, as they are responsible for the acquisition of all data necessary for patient monitoring and evaluation during the pilot period. In this sense, the data flow for the data collection service for smart bracelets and smart insoles is presented, as well as how users interact with these devices.**

***Index Terms*—Digital Transformation, Patient Engagement, Shared Decision-Making, ALAMEDA AI Toolkit, ALAMEDA project**

I. Introduction

Many technological advances have been made in medicine, and neurological diseases such as Parkinson's disease (PD), multiple sclerosis (MS), and cerebral vascular accident (STROKE) have benefited greatly from the digital health revolution. Due to the need for care, as well as the immediate intervention and the small number of professionals in the field of neurologists, the role of telemedicine has become essential in the acute care of cerebrovascular diseases based on scientific evidence [1].

Digital therapy in neurological diseases would involve covering many aspects of a patient's health, providing an approach to the whole person by tracking and analyzing the critical dimensions of health [2]. There is a great need for digital therapy to facilitate lifestyle changes and to address both motor (e.g., walking) and non-motor (e.g., sleep, anxiety) issues. Digital therapy involves the use of digital technologies in conjunction with evidence-based medicine, in order to streamline treatment and personalized patient intervention. This approach helps to improve access to evidence-based interventions and gives patients with neurological problems greater control and accuracy over their treatment.

Digital tools such as smartphones, equipped with accelerometers, gyroscopes and global positioning technology (GPS), are widely available and used daily by over 6 billion people worldwide [3]. Digital tools provide an opportunity to objectively, frequently and remotely assess people with movement disorders in a variety of settings. These digital tools allow the identification of relapse risks and can detect the progress of the disease, leading to the development of new therapies and improved clinical management [4]. Wearable devices can have a wider range of sensors, including electromyography, electrocardiography, temperature sensors, magnetometers and more. Studies with wearable sensors and smartphones were also conducted on large groups of participants, proving a good acceptance of these devices by them [5]. Therapeutic strategy, the need for early and timely intervention in patients with Parkinson's, multiple sclerosis, and stroke - PMSS - remains a challenge in developing new treatment options that also consider personalized pathways.

The ALAMEDA project aims to create prototypes for personalized healthcare systems for people with PMSS, based on artificial intelligence (AI) decision-making models that can be adjusted to cover a variety of issues of these brain diseases. Adequate assessment of the impact of rehabilitation on patients with PMSS remains a challenge for the health system. New approaches are needed to develop new treatment options, with a particular focus on rehabilitation treatments for patients with PMSS, and to design personalized pathways to improve quality of life. Such an application can give healthcare professionals the ability to customize interventions based on personalized data, as well as pharmacological therapeutic recommendations and recommendations for a healthy lifestyle.

In this context, ALAMEDA adopts the guiding principles of Digital Transformation, to address activities, processes, skills, and organizational models to fully capitalize on the changes

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and opportunities of the proposed combination of digital technologies. The active involvement of the people monitored will be central point in designing the system. It is proposed to use a new generation of technological developments integrated with smart home technology to monitor patients' health parameters, e.g. modern smartphones, which come with multiple sensors, will be used to monitor different patient parameters.

This paper presents the ALAMEDA infrastructure architecture and all processes to support the dedicated AI toolkit and the data flow for the data collection service for smart bracelets and smart insoles and interactions with these devices.

The paper is organized as follows: Section 2 presents existing similar solutions. The ALAMEDA AI Toolkit is described in Section 3. Conclusions and future work are detailed in Section 4.

II. Related Solutions

Digital health involves the use of digital technologies that address health, healthcare, and society to make healthcare more efficient [6]. The use of electronic health records, mobile applications, and portable devices provides a meaningful approach and makes clinical trials more pragmatic and effective. Collecting physiological or multiparametric data directly from patients in near real-time can shorten the time to detect an event that suggests a relapse or occurrence of a negative event, with the possibility of immediate intervention [7]. Numerous mobile applications have been developed for the primary and secondary prevention of stroke. Such examples of smartphone applications are the Stroke Riskometer which models the risk of stroke of 5 to 10 years using data from Interstroke study [8].

As the number of wearables and implantable devices increases, so will the ability of specialists to perform sophisticated digital phenotyping, which may in some cases, be more reliable indicators of health than traditional assessment tools or reported results by the patients (PROMIS-10). Technology-based clinical trials have the potential to transform the generation of medical evidence [9]. The use of electronic health records, mobile applications, and portable devices provides a meaningful approach and makes clinical trials more pragmatic and effective.

The technologies used include methods of analytical and artificial intelligence (AI) (e.g. machine learning and symbolic reasoning). Studies have shown improvements in physical activity, eating habits, and adherence to medications [10]. MedRhythms Inc., a digital therapeutic platform aims to improve walking outcomes by digitizing a well-established [11]. Digital walking training therapy includes a sensor worn on the shoe, a smartphone that transmits the acoustic signals through the headphones worn (bottom left) by the patient. Digital therapy is not limited to approaches that address the motor aspects of the disease. Non-motor aspects of neurological disorders can also be effectively addressed through digital means. One of the most studied approaches in this field is cognitive-behavioural therapy administered remotely [12].

Digital technology has enormous potential to transform clinical research and care into neurological diseases. Neurological diseases such as Parkinson's disease, multiple sclerosis, stroke, are particularly complex, characterized by a wide range of motor and non-motor symptoms. This complexity, combined with the lack of objective biomarkers of disease progression, poses a challenge in assessing disability and progression. Traditional assessment scales are subjective, episodic, and usually limited to personal visits. Traditional scales are limited and inadequate to capture fluctuations in symptoms and are unable to provide a comprehensive assessment.

The application of digital technology in neurological disorders has demonstrated the accuracy of identifying patients at high risk for the disease, quantifying specific motor characteristics, predicting clinical events in these diseases, informing clinical management and generating new perspectives.

Shared Decision Making (SDM), a way to empower patients, is defined as an approach in which clinicians and patients share the best information available when making clinical decisions and in which patients are supported to consider options for obtaining preferences. Current models of medical decision-making for brain diseases need to take into account the following issues: therapeutic strategy; avoiding significant delays before a person with symptoms sees a neurologist for diagnosis and treatment; the need for early and timely intervention; a full range of therapies that can reduce disease activity improves the chances of finding the best option for each person with brain disease. To achieve these points, regular monitoring of disease activity is fundamental and a cornerstone of the strategy to improve the current state of decision-making [13].

There are barriers that may limit the adoption of digital therapy [14]. Many digital therapies are accessed through smartphones. Although this suggests a relatively high prevalence of smartphone use among older adults, about 1/3 of those over 70 do not use a smartphone, limiting access to many digital therapy options in this subgroup. Low adoption of digital devices beyond smartphones. Mention should be made of the digital divide [15]. In addition to these global barriers, there are some problems specific to neurological disorders, motor, and cognitive impairments.

In this context the ALAMEDA project (Bridging the Early Diagnosis and Treatment Gap of Brain Diseases via Smart, Connected, Proactive and Evidence-based Technological Interventions) proposes a monitoring solution for patients with PMSS, using multiple sensors and specific applications to collect information about health and lifestyle aspects, activity level, sociability, and mood. ALAMEDA proposes a complete infrastructure to contribute to the vision of digital transformation for healthcare delivery and contribution to key aspects of PMSS care journeys.

III. ALAMEDA Project

ALAMEDA is an ambitious interdisciplinary project, aiming to transform the entire future of medical research supported by advanced Internet of Things (IoT) technology and data

science, especially Big Data and AI. Prediction of the temporal evolution of a patient's disease status as early as possible is one of the most critical desires of medicine worldwide. Until now, a doctor would need to have access to a particularly large number of patients and cooperate with a team of numerous experienced researchers with expertise on mathematics, statistics, information technology (IT), artificial intelligence, and even electronics, in order to stand a chance to perform efficient research on real-time monitoring and predicting critical variables of a specific disease. The large-scale adoption of IoT technology has enabled the efficient and unobtrusive collection of a multitude of data types from large cohorts of patients. At the same time, global open data strategies have allowed access to datasets that can support meaningful research results, while data science and the advanced tools created for Big Data enable efficient processing of all available information.

ALAMEDA aims to develop guidelines that use the principle of shared decision-making to achieve a co-designed participation experience in the ALAMEDA pilot studies for patients with PMSS. The ALAMEDA Shared Decision-Making Model for the Assessment of Brain Disease is based on the MULTI-ACT Patient Engagement Model [16]. One of the key aspects of the governance methodology developed is that patients are seen as key stakeholders in healthcare research and innovation processes.

The data collection process from patients, called the Data Collection Journey, participates in the ALAMEDA pilot studies, either automatically (via wearable devices) or at the request of the patient (questionnaires, user input requirements, etc.). Thus, there are two important sources of data: wearable devices and smartphone applications that allow the collection of patient-reported outcomes.

The ALAMEDA AI Toolkit is a user-friendly "gateway" for interested third-party stakeholders and the overall community that will use the ALAMEDA AI-powered services. The toolkit will take the form of a web-based platform for hosting the AI-enabled services and modules, along with the accompanying documentation.

A. ALAMEDA AI Toolkit

The ALAMEDA AI Toolkit will supply a wider range of medical doctors, researchers, and healthcare professionals of various levels of competence and technical knowledge, by providing them with an arsenal of powerful AI-based tools for monitoring and predicting the progress of brain diseases.

The design of the AI toolkit is based on a multi-level process that starts with data collection and ends with the integration of different Machine Learning (ML) models. Proper data collection, pre-processing, annotation, benchmarking, training of ML models over collected annotated data are very important components of the AI toolkit. ALAMEDA AI Toolkit is composed by the 4 levels [17] that are ahown in Figure 1:

1) **Level 1 - Data Collection**: The quality of data collected plays a crucial role in determining the accuracy of the prognostic and diagnostic abilities of the AI applications. Therefore, data collection is essential for the successful development of such applications, acting as the "spinal cord" of the process. In order to ensure that the data is collected accurately, it is important to adhere to certain principles. To achieve the project's objectives, several principles are adopted: (i) it is important to collect a suitable number of samples for each class or predictive variable, (ii) data collection should involve multiple time series experiments with varying degrees of frequency, (iii) annotation and proper benchmarking of the collected data.
2) **Level 2 - Data Annotation and Pre-Processing**: The accuracy of machine learning and deep learning models relies on the data annotation. Thus, proper annotation enhances the predictive quality of AI algorithms. Therefore, it is crucial to ensure that the annotation of the data is carried out with the targets of prognosis and diagnosis set by medical experts in mind.
3) **Level 3 - Data Analytics using ML/DL**: At this stage, different ML and DL models are trained over the data annotated at Level 2. Various ML/DL concepts, such as convolutional neural networks (CNNs), CNN-based transfer learning, generative adversarial networks (GANs), reinforcement learning, and sequence learning, can be incorporated to achieve the goals of bridging early diagnosis and treatment.

Fig. 1. Core building blocks of the AI Toolkit [17]

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4) **Level 4 - Integration of Trained Models with AI Toolkit**: All the modules are integrated into the AI toolkit to work collectively and effectively, providing mutual compatibility and cohesiveness among different modules.

B. Initial Analyse

The software developed in the ALAMEDA project should be easy to be deployed at the pilots level. It should allow analyzing data locally without uploading them to a server or cloud infrastructure, ensuring compliance with GDPR and EU data privacy regulations. It needs to integrate visual analytics and automated reports. Also, it is feasibile to have an easily extendable modular design, allowing adding their own modules and train existing modules on their datasets.

The analysis of the prediction targets identified by ALAMEDA medical partners is a good place to start. Two critical documents that indicate these prediction targets are the following:

- 1) The predictor and inferred variables - it contains the full list of variables, both patient-generated (predictors) and resulting from clinical tests (inferred). Each variable can be a free numeric value or a discrete one (with values from a fixed sized enumeration). The goal is to use the history of predictor variables (over the past 3, 6, 12 months) to try and predict the result of an upcoming clinical test. All the prediction needs are in fact classification needs, which is a critical factor for the type of AI tools (for example the type and size of neural networks and respective training techniques) we need to include. Within the predictor variables there is a subset of variables, which will themselves be the result of a classification from direct sensor input:
    1) Gait pattern: classification task using input from smart bracelet, smart shoes, smart watch and smart belt.
    2) Facial Expression Analysis: image classification task using input from the front facing smartphone camera.
    3) Text Message Sentiment Analysis: sentiment classification task applied to the content of the conversation a user is having with the ALAMEDA Conversational Agent.
- The Intra-patient progress/regress prediction targets list - it defines sets of cumulative conditions, which indicate a worsening or an improvement of the situation of a patient. These criteria will be used to label a subset of the patient data over a given period of time as representing a progress or regress in their situation. This is currently defined for the Stroke pilot, as it is easier to define such criteria for this affection.

C. Smart insoles

The Novel Loadsol sensors enable mobile measurement of the normal ground reaction force on the plantar surface of the foot. The system can be used both for static and dynamic measurements, to accurately quantify the forces generated between the foot and the shoe. Within the Patient Data Collection Journey, this device captures data that informs the values of:

1) Gait metrics: e.g. step count, stride length, walking speed, cadence
2) Movement and walking patterns: e.g. hypokinesia detection (for the PD pilot), detection of leg-centric physical rehabilitation exercise execution (for the Stroke pilot).

1) Architecture and Data Flows: The data flow for the Smart Insole Data Collection Service is shown in Figure 2. Two types of users interact with the service: the pilot supervisor (role played by medical and/or technical partners of the project) and the pilot user (the actual patients).

Before use, each insole pair needs to be configured (step 1) and tailored to the patient who is going to wear it (e.g. weight of the patient needs to be configured to ensure proper normal force readings). Each time a measurement is performed, data is synchronized to the Loadsol-S Android Application running on the patient smartphone (step 2). At the end of a wear period, data from the smartphone is retrieved by the pilot supervisor (step 3) and stored in raw form in the ALAMEDA Cloud (step 4). During the wear period the patient has the option to use the ALAMEDA Digital Companion to perform annotation (type and start / end times) of specific activities performed during the intensive monitoring period (step 5). The ALAMEDA Platform combines raw data with the annotations (step 6), which can then be exploited by algorithms that are part of the ALAMEDA Gait Analysis Toolkit (Step 7).

2) Timeline of Data Collection: The Smart Insoles are part of the set of devices worn by the patients during the intensive (special) monitoring periods which are scheduled at specific milestones for each pilot study, as follows:

1) PD study: continuous daily wearing for a maximum of 8 hours / day, for the duration of one week prior to each 3-month clinical visit milestone.
2) Stroke study: continuous daily wearing for a maximum of 8 hours / day, for the duration of two weeks prior to every 6-month clinical visit milestone.
3) MS study: continuous daily wearing for a maximum of 8 hours /day, for the duration of two-three weeks prior to every 6-month clinical visit milestone.

3) Data Models Description: The smart insoles capture data related to the ground reaction force (the force with which the ground pushes back on the foot of a person during walking) measured in Newton (N). The insoles have two force sensitive areas, one for the forefoot and one for the heel. Using these sensors the following raw data and aggregated data points can be extracted:

1) Force left / right foot (N) - Ground reaction force measured for the whole foot during a step cycle;
2) Force left / right heel (N) - Ground reaction force measured for the heel during a step cycle;
3) Force left / right forefoot (N) - Ground reaction force measured for the forefoot during a step cycle;

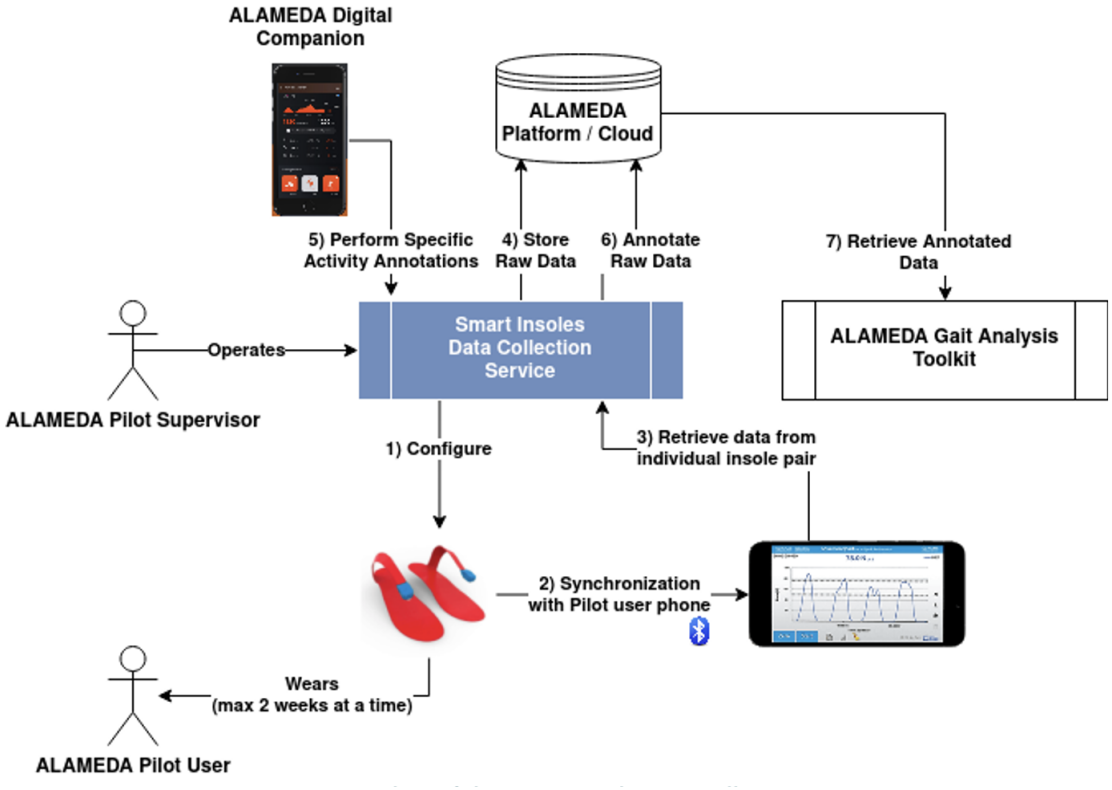

Fig. 2. Data flow of the smart insoles - data collection service.

4) Loading Rate (N/s) - The speed at which the normal force is applied to the body;
5) Force Time Integral (Ns) - Cumulated normal force values accumulated over a period of time (typically max duration of a step cycle);
6) Cadence (steps / min) - Total number of full steps (left plus right foot) performed within a minute.

4) Scenario of use by the ALAMEDA patient users: Once the sensors have been configured, measurements can be performed. Before each measurement, a small calibration procedure is required to be performed by the patient as shown in Figure 4. The procedure involves unloading the left and right foot in succession, so as to provide the application with a sense of the 0 weight normal force, which might be different from an actual 0 value due to the shoes being fitted too tight.

After the calibration procedure the Start button becomes active in the measurement interface. Once pressed the insoles to continue measuring until stopped or the battery runs out. The insoles are used during select intense monitoring periods defined in the Patient Data Collection Journey.

The base usage scenario is that of simple wearing of the insoles inserted in the daily used shoes and worn for a maximum of 8 hours per day. During the intense monitoring period patients will receive daily morning reminders instructing them where and how to put on the insoles, on hand of video tutorials.

In addition to the base usage scenario, patients who engage in specific activities during the intense monitoring period will be encouraged to use the annotation functionality available in the WellMojo component of the ALAMEDA Digital Companion, to mark the start and end. Specifically, patients can mark the start time, end time and type of a special activity (e.g. physical exercise, 30 min outdoor walk, occurrence of a motor symptom, taking of medication).

The following special activities benefit from the annotation functionality:

1) Stroke pilot: execution of leg mobility physical rehabilitation exercises
2) PD pilot:
   a) execution of the 30 min walk
   b) marking of the occurrence of tremor, dyskenisia or hypokinesia symptoms
3) MS pilot: marking of the occurrence of movement stiffness episodes

5) Integration with the ALAMEDA platform: All data measurements are automatically stored on the smartphone. They can be visualized on the smartphone (see Figure 3) and the Loadsol-S application enables storing in a binary file format which can later be converted into a CSV format using the Loadpad Analysis PC software application.

The extracted CSV files are uploaded in raw form to the ALAMEDA cloud using a secure key-based SSH connection. The files are organized by patient ID and individual days of recording over the respective intense monitoring period. The

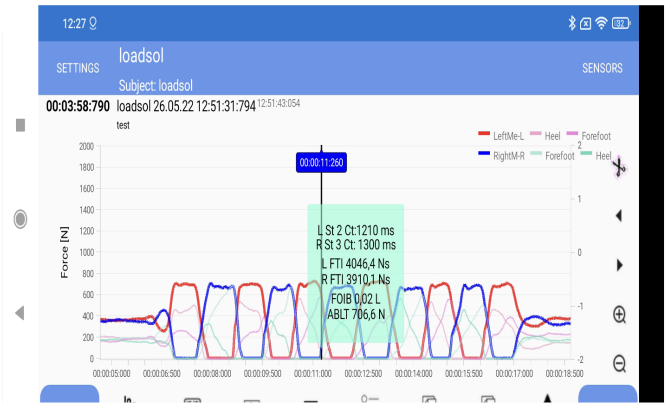

Fig. 3. Visualisation data acquired from insoles.

raw normal force values are required as input to the algorithms within the ALAMEDA Gait Analysis Toolkit, which corroborates information from several sources (smart bracelet, insoles and belt) to perform detection of the performed exercises, detection of walking patterns and reduced mobility periods, as well as extraction of gait metrics.

D. Smart Bracelet

The GENEActiv bracelets are developed by UK company ActivInsights and contain a 3-axis accelerometer sensor, a temperature sensor and a light intensity detection sensor. They are widely used in clinical and observational studies that involve the tracking of movement and activity metrics.

Within ALAMEDA and, in particular, the Patient Data Collection Journey, this device captures data that informs the values of:

1) Gait metrics: e.g. step count, stride length, walking speed, cadence
2) Activity metrics: daily durations of sedentary, low, medium and vigorous activity
3) Movement and walking patterns: e.g. tremor detection, hypokinesia detection (for the PD pilot), detection of physical rehabilitation exercise execution (for the Stroke pilot)
4) Sleep metrics: e.g. time spent in bed, time spent sleeping, wake after sleep onset duration, wake up time, falling asleep time

1) Architecture and Data Flows: The data flow for the Smart Bracelet Data Collection Service is depicted in Figure 4 and is similar to the one described for the Smart Insoles. The same types of user interact with the device: the pilot supervisor (role played by medical and/or technical partners of the project) and the pilot user (the actual patients).

Bracelets need to be configured for frequency of measurement (e.g. 50Hz) and body wear location (step 1). At the end of a wear period, data from the bracelet is retrieved by the pilot supervisor (step 2) and stored in raw form in the ALAMEDA Cloud (step 3). Annotations made by the patient (e.g. performed physical exercises) using the ALAMEDA Digital Companion are also stored in the ALAMEDA Cloud (step 5) and used to characterize the raw data (step 6). Apart from raw data, the Smart Bracelet Data Collection Service extracts daily statistics of summarized activity and sleep (step 4). The annotated raw data can finally be exploited by algorithms that are part of the ALAMEDA Gait Analysis Toolkit (Step 7).

2) Timeline of Data Collection: The Smart Bracelet is also part of the set of devices worn by the patients during the intensive (special) monitoring periods which are scheduled at specific milestones for each pilot study, as follows:

1) PD study: continuous daily wearing on the wrist and nightly wearing on the ankle (to detect effects of restless leg syndrome) for the duration of one week prior to each 3-month clinical visit milestone.
2) Stroke study: continuous daily wearing on the wrist and nightly wearing on the ankle (to detect effects of restless leg syndrome) for the duration of two weeks prior to every 6-month clinical visit milestone.
3) MS study: continuous daily wearing on the wrist for the duration of two-three weeks prior to every 6-month clinical visit milestone.

3) Technical specifications including annotation: Before a wear period begins the bracelet is configured by medical partners by specifying the following important meta-data:

1) The Patient ID, used to identify the user from which the data was collected. The patientid is unique per patient registered in ALAMEDA pilot studies;
2) The wear location during the day: left or right wrist;
3) The sampling frequency: 50Hz for a wear time of at most two weeks, 20Hz for a three week duration (may be the case in for some MS patients).

Configuration and charging is performed using the USB cradle. After configuration, the patient is not required to interact with the device in any way (recharging is also not necessary), other than wearing it as instructed by the medical professionals.

4) Data Models Description: Raw data concerning 6 signals can be retrieved with the frequency specified in the configuration phase (see Figure 4):

1) Acceleration values for X, Y and Z axes measured in gravitational acceleration (g) units. Range: -8g – +8g;
2) Temperature (degrees Celsius) – Range: -25°C - +40°C;
3) Light intensity (lux) – Range: 0 – 3000;
4) Button press (number of presses).

Apart from storing the raw data, the Smart Bracelet Data Collection service contains a set of scripts which adapt and extend existing open-source R and Python scripts that compute day-level summaries of activity and sleep metrics. Since there are several code libraries that are used to perform metric extraction, the final results are associated with meta-data information indicating their provenance.

The activity summary currently includes metrics of:

1) step count
2) non_wear period

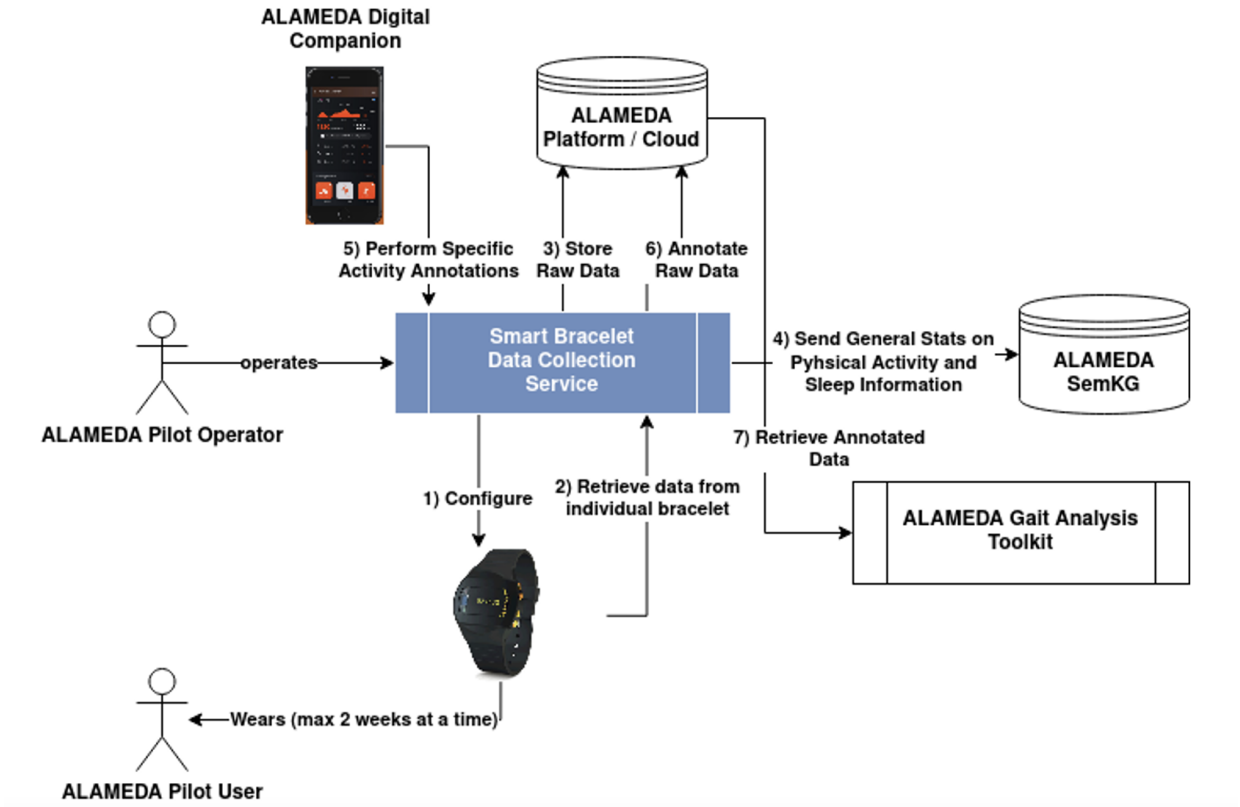

Fig. 4. Data flow of the smart bracelet - data collection service.

3) sedentary / light activity / moderate / vigorous period duration

The sleep summary currently includes metrics of:

1) sleep onset
2) bed rise time
3) total bed time and total sleep time / sleep efficiency
4) total wake after sleep onset duration
5) duration of time until the first wake up after sleep onset

5) Scenario of use by the ALAMEDA patient users: As mentioned, the GENEActiv Bracelet is a device worn by the patient during select intense monitoring periods defined in the Patient Data Collection Journey. The base usage scenario is that of simple wearing of the device on the wrist during the day and the ankle (where required) during the night. The objective in the base usage scenario is to capture activity summaries to a higher granularity. During the intense monitoring period patients will receive daily morning and evening reminders instructing them where and how to put on the device.

The smart bracelet data benefits from the annotation of the following special activities :

1) Stroke pilot: execution of upper limb physical rehabilitation exercises
2) PD pilot:
   a) execution of the 30 min walk;
   b) marking of the occurrence of tremor, dyskenisia or hypokinesia symptoms;
3) MS pilot: marking of the occurrence of movement stiffness episodes.

6) Integration with the ALAMEDA platform: After a wear period the data is extracted from the device using the USB docking cradle and the provided GENEActiv software application running on Windows-based machines. The data is extracted in a binary format which can be read using a number of open source libraries (e.g. GENEAread in R, pygeneactiv in Python).

Data extracted from the GENEActiv bracelet follows two paths of processing and integration into the ALAMEDA platform (see Figure 4):

- Raw data storage: the binary file is uploaded via a secure SSH connection to the ALAMEDA cloud, where it is indexed by patient ID and start and end timestamps of the wear period. The raw accelerometer values are required as input to the algorithms within the ALAMEDA Gait Analysis Toolkit, which corroborates information from several sources (smart bracelet, insoles and belt).
- Activity and Sleep metric summarization: the data is processed by internally developed scripts which adapt and extend existing open-source R and Python scripts that compute activity and sleep metrics. After extraction, the summaries are inserted into the ALAMEDA Semantic Knowledge Graph (SemKG) using the API provided by the toolkit.

IV. Conclusions and Future Work

This research presents the ALAMEDA AI Toolkit, a web-based platform for hosting AI-enabled services and modules. The design principles of ALAMEDA AI Toolkit are based on meeting the requirements of the people involved in this process. ALAMEDA Infrastructure offers an innovative vision of digital transformation for healthcare delivery and contributes to key aspects of PMSS care journeys. The analysis of predictive targets identified in the ALAMEDA project is an innovative and at the same time beneficial feature for medical partners. The technologies and digital tools proposed in the Alameda project for PMSS neurological conditions have the potential to lead to personalized treatment and rehabilitation protocols, with the greatest added value in expanding the monitoring and evaluation services requested by physicians and patients.

As future work, we will enhance the components based on the feedback from the ALAMEDA pilots regarding the integration and development of vital parts of ALAMEDA project. Due to the lack of public data, evaluation of the models will be performed after pilots using data collected through the project.

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