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Digitalization As basic Driver for servitization in Industry and Basic Services” (DADIBAS)

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1 INTRODUCTION

Project Title:	<i>"Digitalization As basic Driver for servitization in Industry and Basic Services" (DADIBAS)</i>		
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2 CONTEXT

The focus of this titled "Wearables: Integration of Human Dimension," looks to incorporating information related to the behavioral aspects of process operators and assessing how recognizing this information can enhance an organization's understanding of its processes.

A significant challenge within this work package is addressing the General Data Protection Regulation (GDPR) due to the nature of the information being considered. Therefore, considerable effort will be dedicated to anonymizing data through digital quasi-identifiers and managing information distribution. The project also intends to explore solutions for securely providing information to digitally asymmetric stakeholders.

Key tasks within WP3 include:

- **Design of mobile apps for data collection from wearable devices:** This task aims to collect data from human operators using wearable devices, such as foot pressure, worker position, and heart rate, to identify their contribution to process variability. The goal is to collect high-frequency data, store it, and merge it with process data, carefully addressing interoperability issues.
- **Workflow for data ingestion from different users/workers:** This task will focus on developing a technological solution to gather multiple data streams from various data brokers, originating from different devices or workers, ensuring scalability and robustness. This solution will also support tasks in A1-WP2 and A1-WP4.
- **Workflow for KPI extraction and interoperability:** This involves transforming raw data in real-time to facilitate proper process flow and enable interoperability, allowing manufacturing partners (including customers, suppliers, and other departments) and their machines to share information accurately and quickly. This task will also serve other A1-WPs.
- **Data Integration & Data availability through DLT:** Connected to the KPI extraction task, this involves implementing solutions for data integration, initially considering Apache NiFi® and Airflow®. IoTA digital identity will be tested to provide digital identity to artifacts, people, and devices for communication, and IoTA stream will be explored for real-time data distribution among stakeholders when system isolation is required.
- **Process Model creation:** The objective is to enhance existing digital models by exposing them to human-related information as additional features, thereby verifying the effectiveness in achieving better-explained processes.
- **Dissemination:** This WP is expected to contribute to dissemination with at least three scientific papers on behavioral data collection, IoT-enriched digital models, advanced real-time data distribution without direct contact, and three international conference presentations. Dissemination within the WP will be closely monitored according to the objectives from A1-T1.2.

- **Reporting & Configuration management:** This task will oversee deliverable production and implement a configuration management solution to control product releases during the DADIBAS project.

The deliverables for A1.WP3 include reports on wearables and digital solutions for context enrichment in predictive models, data integration, interoperability, and communication without contact, and a dissemination report with KPIs. This work package is considered intensive in knowledge creation as it delves into a crucial area for the Industry 5.0 paradigm.

- **D3.1.- Wearables and digital solutions for context enrichment in predictive models [M24]**
This deliverable focuses on the practical application of wearable technology to gather crucial human-centric data. It will outline the design and implementation of mobile applications and digital solutions that collect information from various wearable devices. The core idea is to enrich existing digital models of processes by incorporating this human-generated data as additional features. The aim is to demonstrate how recognizing the behavioral dimension of process operators, through data like foot pressure, worker position, or heart rate, can lead to a better understanding and explanation of industrial processes.
- **D3.2.- Data Integration, Interoperability, and Communication without contact [M30]**
This deliverable will present the developed technological solutions for seamless data ingestion and integration from diverse sources and users within the industrial environment. It will detail how multiple data streams from various devices and workers are gathered and processed, focusing on scalability and robustness. A key aspect is achieving interoperability, allowing for real-time data access and sharing between different manufacturing partners, including customers, suppliers, and internal departments, and their machinery. The deliverable will also explore and present solutions for secure and "contactless" communication and data distribution among stakeholders, particularly utilizing technologies like DLT (Distributed Ledger Technology), such as IoTA digital identity and IoTA stream, especially when system isolation is required.
- **D2.3.- Dissemination report and KPIs [M48]**
This report will summarize all dissemination activities undertaken throughout the project related to A1.WP3, specifically highlighting achievements in knowledge creation within this work package. It will detail contributions such as scientific papers (e.g., technical solutions for behavioral data collection, IoT-enriched digital models and their effects, and advanced real-time data distribution without direct contact) and international conference presentations. The report will also include key performance indicators (KPIs) used to monitor the effectiveness of the dissemination strategy, aligning with the broader project's dissemination objectives.

3 EXPECTED OUTCOMES

Concerning the current report, which is D3.1 the expected outcome involves the design of mobile applications to collect information from various wearable devices for data collection. The goal is to gather data from human operators on factors like foot pressure, worker position, and heart rate, to assess their relevance to stress levels and process variability. This collected data, depending on the variable, should be stored in high frequency and be mergeable with existing process data. The interoperability of these data expansions needs to be carefully addressed.

The following requirements are enumerated:

- Design of mobile apps to collect information from different wearable devices for data collection.
- Collection of data from specific wearables such as pressure in feet (when the operator is walking), worker position, and heart rate (to check the relevance for stress levels).

The idea is not just to

- collect data in high frequency (depending on the variable) but to store them and be able to merge them with process data.
- The interoperability of data expansions will be carefully addressed.

4 METHODOLOGY

The design principles adopted in this research were shaped by the contributions of (*José Osvaldo De Sordi, 2021; Peffers et al., 2007; Venable et al., 2017*). Their design approach encompasses a structured methodology involving problem identification, objective definition, solution development and evaluation, and ultimately, result communication. This method is instrumental in guaranteeing that the resultant artifacts are effective, beneficial, and pertinent to the requirements of stakeholders within a given context. The context may include people, businesses, organizations, and existing technologies that are relevant to the problem. The Design science methodology also helps to identify any potential limitations or challenges that may need to be considered when developing an artifact.

There is a need for a more thorough conceptualization of wearable data within the complex semantic framework of industrial processes. This is especially crucial for understanding interactions between discrete equipment states and human operators, with the goal of reducing discrepancies in comprehending the entire process flow (*Ordieres-Meré & Ortega-Mier. Miguel Ángel, 2024*).

Múltiple physical layers are anticipated, where all pertinent data converge at a personal hub. This hub is responsible for preliminary data processing and subsequent submission to the relevant cloud platform, depending on the device manufacturer or the specific data collection application employed.

According to the proposed framework, the hub layer adds relevant information, since it is in charge of continuously querying the IoT devices attached to socks at the established sampling rate, to integrate the GPS information coming to the phone and, potentially other relevant sensors such as heart rate, leg providing data, etc., while special attention was paid to the General Data Protection Regulation (GDPR) adopted by the EU. In this way, no specific information from people is directly collected, and all the dataset is referred to specific id-tokens provided by neurologists, and they are study based.

Once the data are collected, the setup of the records is prepared to be stored remotely. Then data compression, encryption, and delivery are performed in the cloud, where an Influx DB time series database was selected to store the collected data.

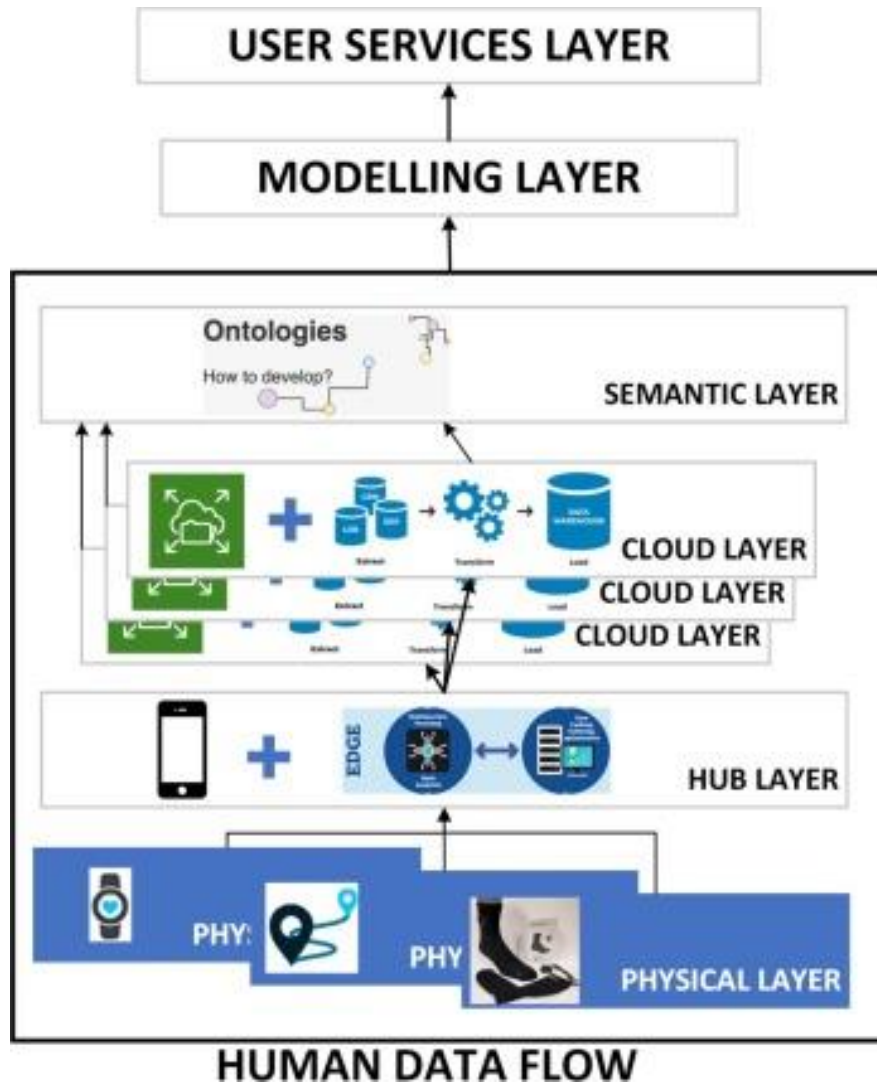


Figure 1.- Reference Framework proposed inside the project.

The attached framework, illustrating the "HUMAN DATA FLOW," highlights the crucial role of a Semantic Layer in connecting disparate data sources and layers to ultimately inform user services. This semantic connection holds significant potential for enhancing data interpretation, facilitating interoperability, and enabling more intelligent applications, particularly in the context of human-generated data.

At its core, the Semantic Layer, through the use of ontologies, provides a structured and formalized representation of knowledge. Ontologies define concepts, their properties, and relationships within a specific domain, allowing for a common understanding of data across different systems and stakeholders. This is particularly vital in the "HUMAN DATA FLOW" framework, where data originates from diverse "PHYSICAL LAYERS," such as wearables (e.g., smartwatches, foot pressure sensors). Without a semantic layer, integrating and making sense of such heterogeneous data, collected at the "HUB LAYER" and processed through various "CLOUD LAYERS", would be a complex and often manual task.

The potential of this semantic connection extends to improving data discoverability and reusability. By semantically annotating data, it becomes easier for different applications and users to find, understand, and utilize the information, even if they were not the original creators. This is crucial for building robust "MODELLING LAYERS" that can derive meaningful insights and for enabling sophisticated "USER SERVICES LAYERS" that can deliver personalized and context-aware applications. For instance, a semantically enriched human data flow could enable

predictive health analytics, optimize ergonomic work environments, or inform adaptive training programs by seamlessly integrating physiological data with operational contexts. Furthermore, this approach aligns with the FAIR (Findable, Accessible, Interoperable, Reusable) data principles, a cornerstone of modern data management and scientific research, as highlighted in numerous well-reputed journals.

5 RESULTS

According to the Section 3 and 4, we have focused on the design of mobile applications to collect information from various wearable devices for data collection with the clear vision of respecting the proposed framework.

Inside DIGEST project we have addressed the design and implementation of several apps to integrate the human interaction from both, motion but also cognitive dimensions.

5.1 Tracking Gait with Wearable sensors

The integration of human data, particularly gait analysis from operators, into process operations offers significant interest in enhancing organizational knowledge and optimizing industrial efficiency. By tracking an operator's gait, a wealth of physiological and behavioral information can be collected, providing novel insights into their physical status, fatigue levels, and even their interaction with machinery and the work environment.

This granular data, often gathered through wearable devices like smart insoles or other sensors, can reveal subtle changes in an operator's movement patterns that might indicate the onset of fatigue, stress, or even musculoskeletal strain. For example, deviations from a baseline gait could signal increased effort or discomfort, which, if unaddressed, might lead to reduced efficiency, errors, or even injuries. This direct monitoring of human physiological responses provides a real-time, objective measure that traditional observational methods often miss.

Furthermore, integrating gait data with existing process data allows for a more comprehensive understanding of process variability. Human operators are often a significant source of variability in Key Performance Indicators (KPIs). By understanding how an operator's physical state, as reflected in their gait, correlates with process outcomes, organizations can identify previously unrecognized intrinsic variabilities in their operations. This deeper insight enables the development of more accurate process models, leading to better-explained processes and more effective interventions (see Figure 2).

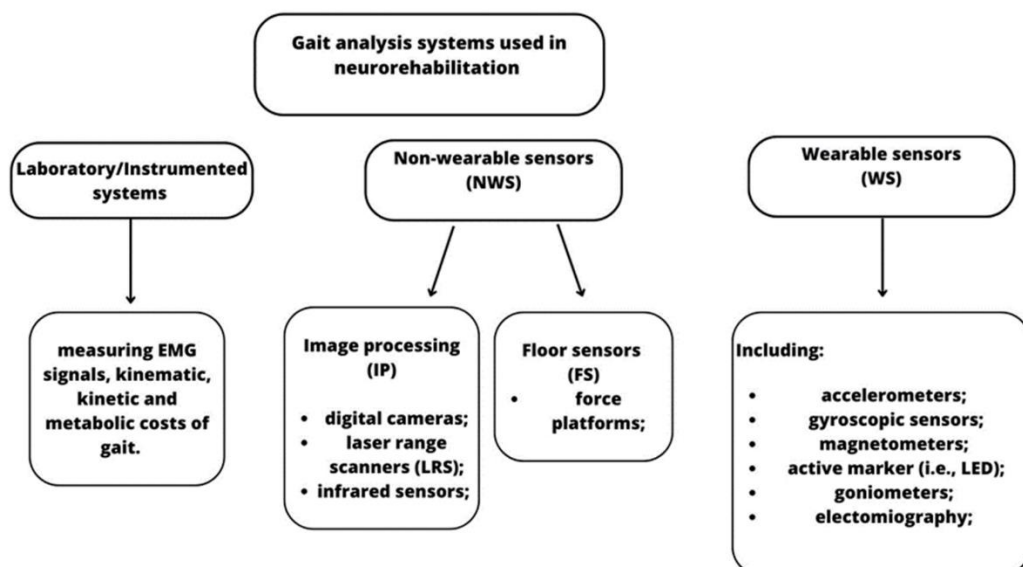


Figure 2.- General scheme addressing Gait analysis.

For instance, if specific gait patterns are consistently linked to a decrease in product quality or an increase in energy consumption, targeted interventions can be designed to support the operator or optimize the process to mitigate these effects. Ultimately, tracking gait from operators contributes to a more holistic, human-aware approach to process management, aligning with the Industry 5.0 paradigm that emphasizes the integration of human elements into digital representations of processes.

Traditionally, gait analysis has depended on specialized laboratory equipment, requiring patients to travel to clinics with costly instrumentation. However, advances in sensor technology have dramatically expanded the reach of health monitoring, making it possible to gather detailed, high-frequency physiological and movement data in free-living conditions through wearable and non-wearable devices (Bonanno et al., 2023; Celik et al., 2021).

Wearable sensors are increasingly valued in clinical and research domains for their portability, cost-effectiveness, and ability to provide continuous, real-time monitoring. Their adoption has grown in neurological rehabilitation (Celik et al., 2021; Salchow-Hömmen et al., 2022), orthopedic recovery (Chowdhury et al., 2022), sports performance monitoring [6], elderly mobility monitoring (De Fazio et al., 2023), as well as for chronic disease management and remote monitoring scenarios [8, 9]. However, despite their considerable potential, wearable sensor applications remain fragmented and often restricted to research contexts due to challenges in integrating multiple sensor data streams into a cohesive health monitoring system and continuous home monitoring of multiple health metrics, standardizing data interpretation and management (Bonanno et al., 2023; Majumder et al., 2017). Patients frequently use separate devices for different physiological metrics, forcing clinicians and caregivers to manually aggregate data, limiting scalability and clinical adoption.

HealthyWear was developed to address these limitations, by providing a unified cross-platform mobile application enabled by the Internet of Things that connects to multiple wearable devices simultaneously and streams data to the cloud for real-time analysis. The system addresses key challenges in physical therapy and telemedicine, where clinicians and therapists need continuous feedback on patient gait quality to adjust exercises or assistive devices, and physicians need up-to-date vital signs during rehabilitation. By consolidating gait data from smart socks and motion sensors, with physiological metrics (e.g. heart rate, SpO₂) from a smart band, HealthyWear delivers a more comprehensive health overview than any single wearable could provide.

The architecture of HealthyWear emphasizes modularity, scalability, and accessibility, enabling adaptation for broader clinical and research applications (see Figure 3). Its modular Bluetooth Low Energy (BLE) integration, real-time data buffering, and robust cloud synchronization mechanisms support seamless deployment across use cases ranging from orthopedic rehabilitation and elderly mobility monitoring to sports, operators at work, injury prevention, or performance tracking and cardiovascular monitoring (Chowdhury et al., 2022; De Fazio et al., 2023; Stavropoulos et al., 2020). Employing Flutter for cross-platform mobile development allows HealthyWear to reduce technical barriers and ensure reliable deployment on both Android and iOS devices, facilitating widespread use.

HealthyWear is built on a modular, hybrid architecture that combines cross-platform flexibility with optimized native performance. Developed with the Flutter SDK and Dart programming language, the core application logic and user interface are shared across Android and iOS, minimizing development and maintenance overhead while ensuring consistency for users and clinicians.

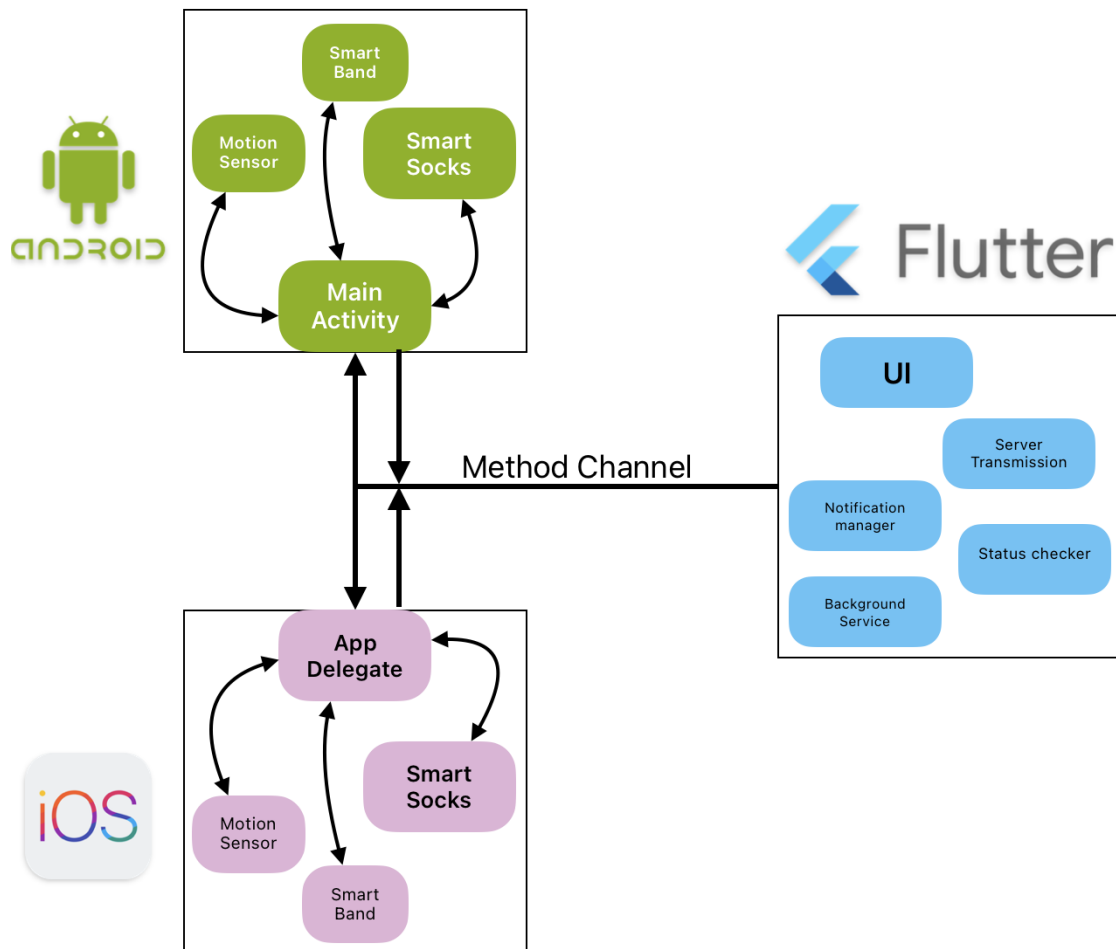


Figure 3.- Architecture of the app.

To achieve robust access to hardware specific features, platform-dependent operations such as Bluetooth communication, sensor data handling, and file system access are implemented natively (Java on Android, Swift on iOS) and exposed to the Flutter framework via Method Channels. This hybrid strategy ensures that the app can leverage the full capabilities of each platform without sacrificing code reuse or maintainability.

The modular software architecture, which separate native modules for Android (MainActivity) and iOS (AppDelegate) interact with wearable devices using native BLE APIs. After receiving, processing, and buffering data, these modules tag data packets with relevant metadata before handing them off to the Flutter layer. The Flutter layer manages local storage, periodic uploads to the server, and confirmation-based deletion of transmitted files, providing a robust pipeline that minimizes the risk of data loss due to network interruptions or device issues.

As shown in Figure 4, HealthyWear as part of a broader end-to-end IoT system, where wearable devices (smart socks, motion sensors, wristbands) connect via BLE and continuously transmit raw sensor data to the mobile application. HealthyWear buffers, serializes, and stores this data locally; at configurable intervals (default one minute), it securely uploads compressed data batches to a cloud server using HTTPS. A Python-based middleware receives and decompresses the data, which is validated and stored in an InfluxDB time series database. Real-time and historical analytics are made available through a Grafana dashboard, supporting continuous monitoring, research, and clinical decision support for a variety of stakeholders.

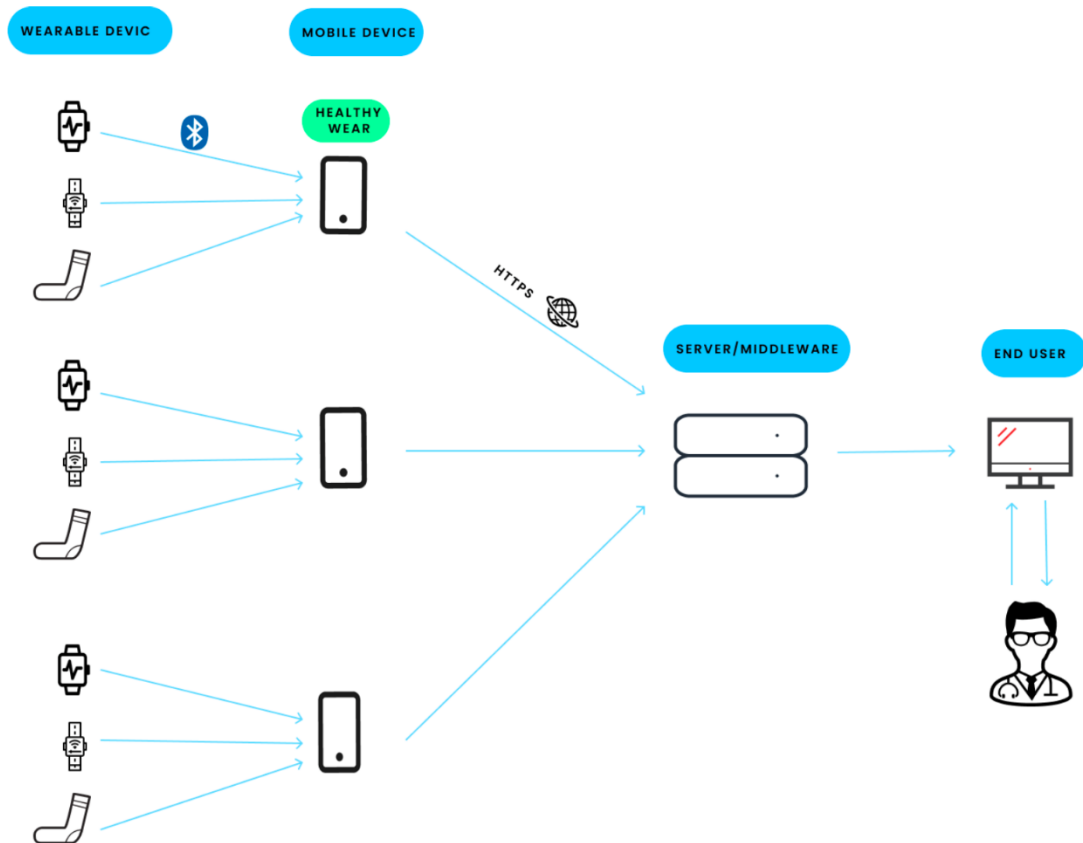


Figure 4.- IoT Gait Monitoring System Architecture.

The user interface is designed for simplicity, accessibility, and usability, especially for older adults and individuals with mobility impairments (Figure 5). The dashboard prominently displays device connection statuses using intuitive color-coded icons and real-time animations, giving immediate feedback about system activity. Large, touch friendly controls reduce the risk of user error and make it easy for anyone to connect or disconnect devices.

In terms of user experience design, HealthyWear prioritizes minimizing user interactions to the greatest extent possible. Instead of requiring traditional multistep workflows that involve scanning, pairing, or repeated confirmations, the app uses a one-button operation. The user simply selects, for example, the right foot sock and brings the phone close to it; the system then automatically handles the connection of the device, data reception, processing, buffering, and secure server transmission without additional user input. When the test is finished, a single button press disconnects the device, avoiding redundant steps and simplifying the process.

The interface is multilingual (initially English and Spanish), and careful attention has been paid to color contrast, font size, and layout spacing to ensure clarity and minimize visual strain. Proactive alerts notify users of critical events such as low battery or device disconnection, enabling quick response without frustration. HealthyWear's interaction paradigm avoids multi-step processes by using a one-button operation for connection, data capture, and session management, which streamlines the workflow for users with reduced dexterity, cognitive limitations, or other accessibility challenges.

HealthyWear uses a secure, privacy-preserving reference code system for user authentication. The clinician generates a unique code with checksum via a secure web portal, linking it to the patient's clinical record but never transmitting or storing personal identifiers in the app. Upon code entry, the app validates its integrity and activates its interface, ensuring that only

authorized patients and sessions are enabled. This mechanism is compliant with healthcare privacy standards, supporting anonymized aggregation and analysis of health data.

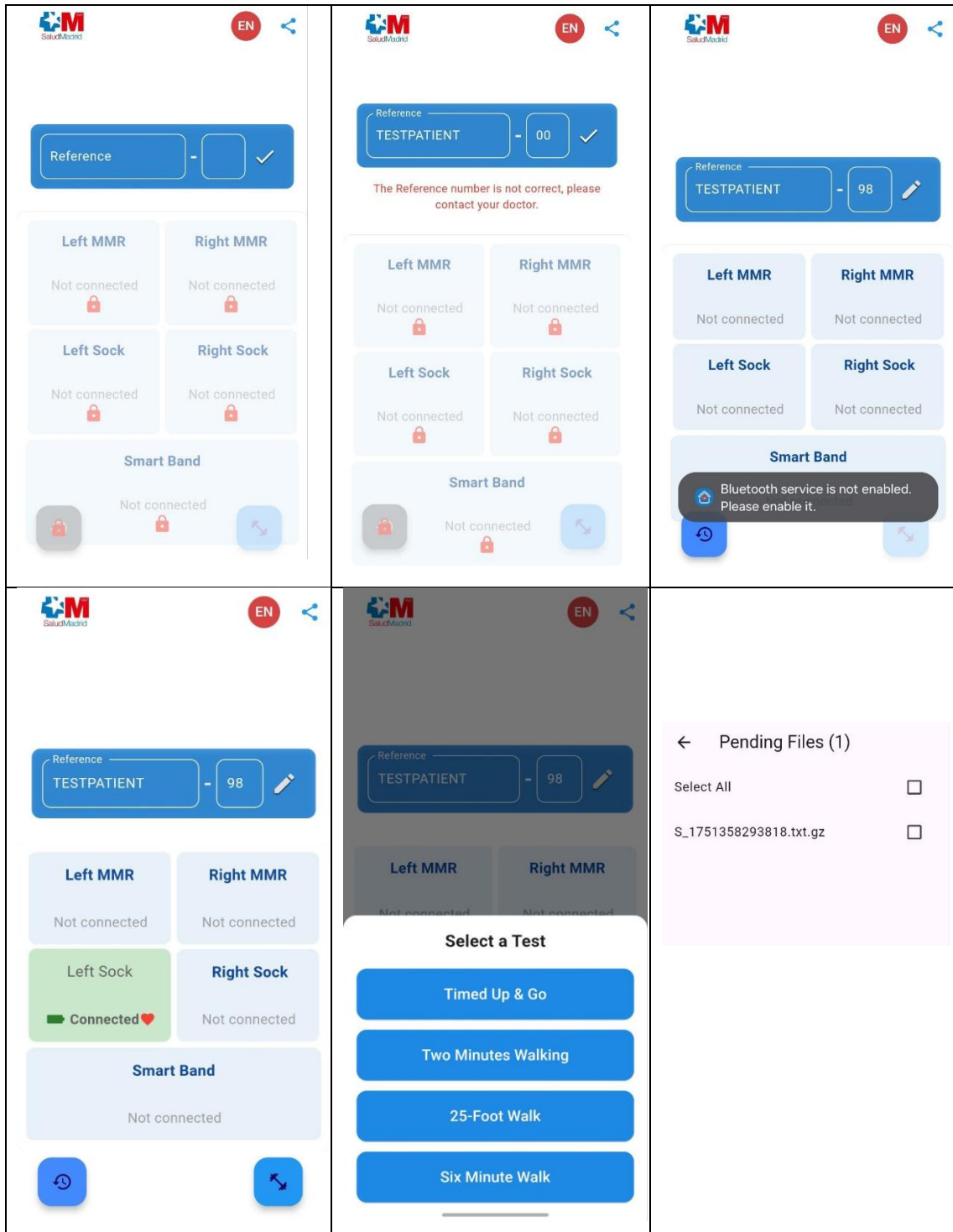


Figure 5.- Screenshots of the elaborated app.

Device management is streamlined for minimal user intervention. After selecting a device type (e.g., smart sock), the app initiates a BLE scan and connects automatically to the nearest device based on signal strength, eliminating the need for manual pairing or confirmation. Subsequent device selections reuse recent scan data for rapid connection. Once connected, the app subscribes to the data stream, initiating real-time acquisition and secure transmission without further user action. This workflow has proven effective in real-world clinical settings, supporting one-button operation and minimizing cognitive load.

Each connected device streams data specific to its modality and body placement. Smart socks provide plantar pressure, acceleration, angular velocity, and magnetic field data. Motion sensors yield orientation, gyroscope, and magnetometer readings, while wristbands supply heart rate and blood pressure. Sampling rates are high, ranging from 50 to 100 Hz, allowing for fine-grained movement analysis. Data are decoded from raw binary into standardized, structured formats for aggregation and visualization.

```
696,773,710,-0.105469,0.101563,0.988282,-0.009344,0.186880,-0.616704,-8.960000,-2.2
40000,-8.960000,1711268322063,Left
705,541,849,0.062500,-0.117188,1.031251,-0.429824,0.289664,-0.420480,-3.360000,-7.8
40000,0.000000,1711268322066,Right
695,773,710,-0.101563,0.105469,0.988282,-0.009344,0.177536,-0.635392,-8.960000,-2.2
40000,-10.080000,1711268322067,Left
705,541,849,0.062500,-0.117188,1.031251,-0.429824,0.289664,-0.420480,-3.360000,-7.8
40000,0.000000,1711268322068,Right
```

Figure 6.- Serialized Data Sample

Given the high frequency and volume of data, HealthyWear uses a synchronized buffering mechanism. Incoming data packets are tagged with rich metadata, enabling robust multi-sensor data fusion and traceability. enabling robust multi-sensor data fusion and traceability.

Once the buffer threshold is met, the app serializes and compresses the data, storing it temporarily in encrypted device memory (see Figure 6).

At regular intervals, the app uploads compressed data to the backend via HTTPS, ensuring security and integrity of sensitive health information. Upon successful upload and server acknowledgment, local files are purged to minimize storage footprint and privacy risk. If the network is unavailable, the app retains data and retries automatically upon reconnection. Users may also manually share data in special circumstances by using in-app share feature, preserving data availability under all conditions.

The backend middleware validates, decompresses, and parses uploaded files before storing records in InfluxDB. Data are then visualized in Grafana dashboard (see Figure 7).



Figure 7.- Grafana dashboard over InfluxDB.

The end-to-end pipeline is scalable and secure, adhering to best practices for healthcare data governance and real-time monitoring. HealthyWear complies with GDPR and ethical standards, ensuring user privacy through anonymized tokens and HTTPS-secured data transfer. Its data collection protocols have been ethically approved by the Technical Committee of Universidad Politécnica de Madrid Ethics Committee, guaranteeing informed consent and patient confidentiality.

5.2 Cognitive assessment TMT app.

The MS-dTMT is a mobile application developed with Flutter for cognitive testing. The project implements cognitive assessment tools such as the Digital Trail Making Test (Digital TMT), aimed at providing a convenient and reliable solution for cognitive function assessment.

The MS-dTMT application, built with Flutter, represents a significant step forward in accessible cognitive assessment, specifically focusing on the Digital Trail Making Test (Digital TMT). Its core purpose is to offer a convenient and reliable digital solution for evaluating cognitive function, moving beyond traditional paper-based methods.

The design philosophy behind MS-dTMT is rooted in a "feature-first architecture". This means the application's development is organized around distinct, independent functionalities, which contributes to a more modular and manageable codebase. This architecture is further detailed by its clear organization, dependency rules, integration with GetX, and a well-defined folder structure, all contributing to the benefits of this approach.

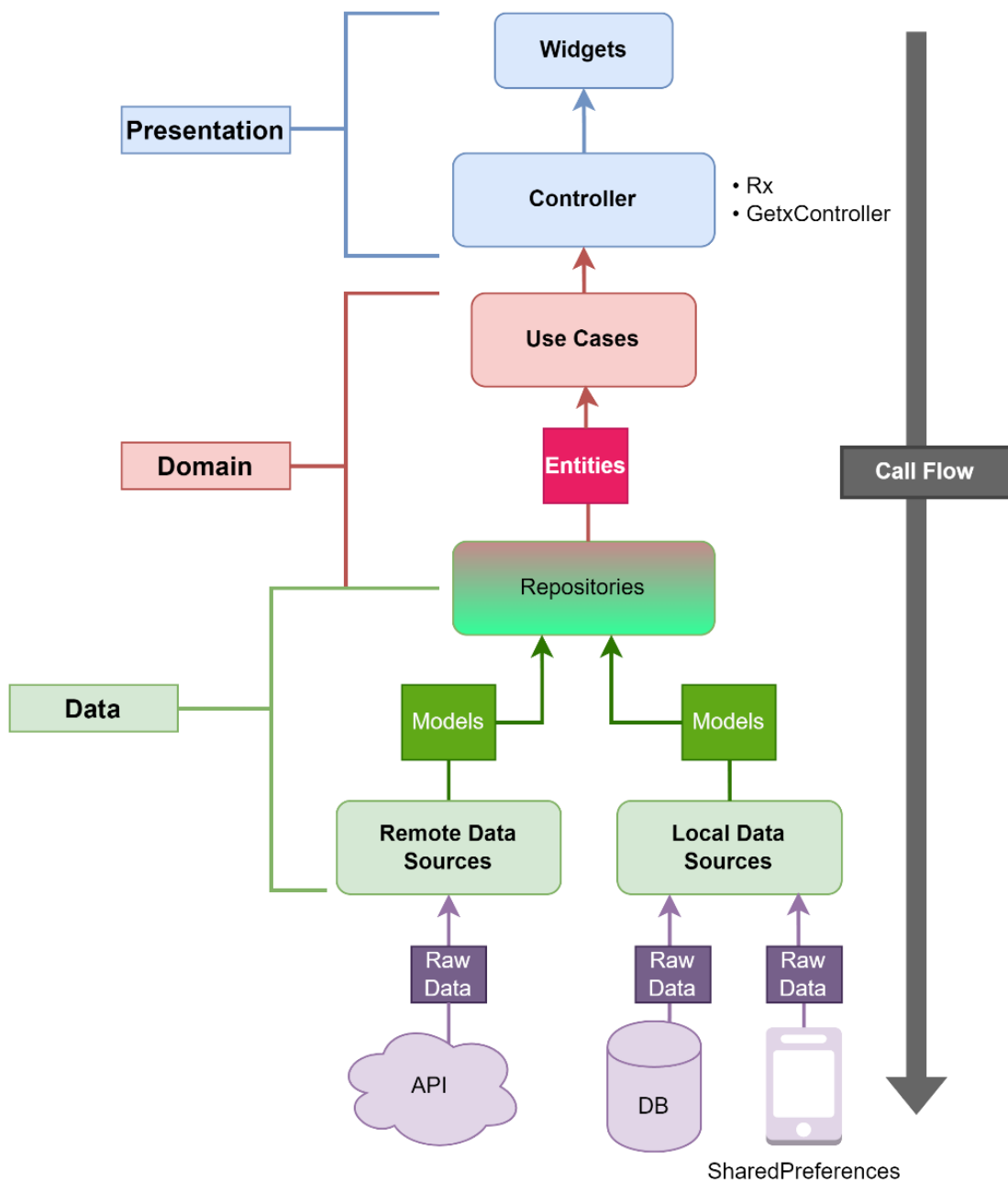


Figure 8.- Clean Architecture layers.

From a structural perspective, the application is divided into several key modules, each serving a specific purpose within the user's journey. These include a Splash module for initial loading, a Home module likely serving as the central navigation point, a dedicated Trail Making Test module where the cognitive assessments are administered, and a User module, presumably for managing user profiles or data. Beyond these feature modules, the app also incorporates essential "Application Layers," such as a Configuration Layer for managing settings, a Shared Components Layer for reusable UI elements and logic, and a Utilities Layer for common functions, underscoring a well-thought-out and maintainable design.

While the documentation found in provides a clear overview of the app's purpose <https://2025-peng-xiaoyang-cogtests.readthedocs.io/en/latest/index.html>, architectural choices, and modular breakdown, a deeper dive into the specific user experience of the Digital TMT itself, including how the test is administered, how user interactions are captured, and the algorithms employed for scoring and analysis, would further enrich the understanding of its full capabilities. Similarly, details on data storage, security protocols for sensitive cognitive data, and potential integrations with other health platforms would provide a more comprehensive picture of the application's overall utility and impact.

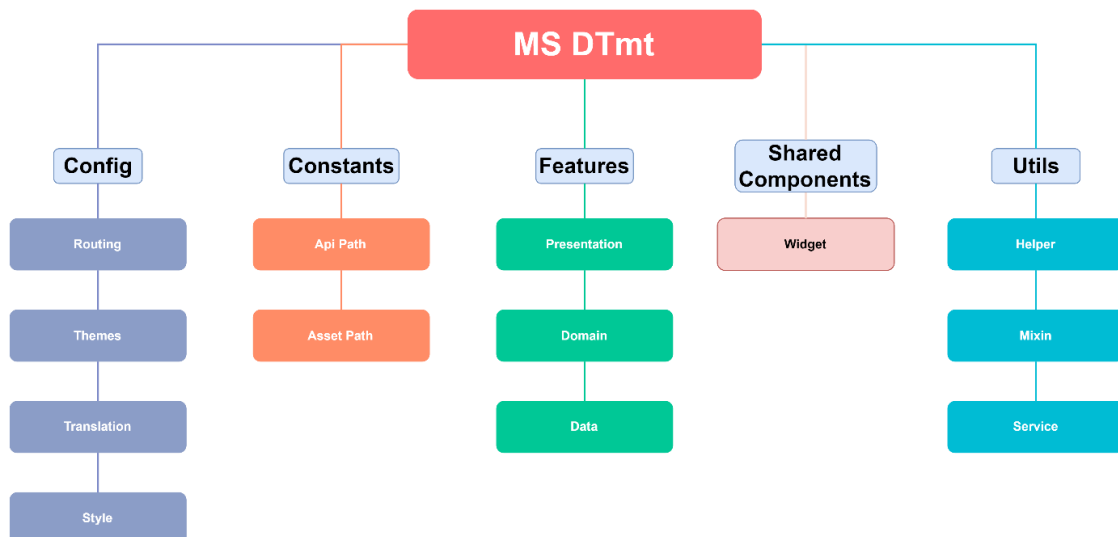


Figure 9.- Project structure.

5.3 Cognitive assessment SDMT app.

The SDMT (Symbol Digit Modalities Test) app is a specialized mobile application designed as a standardized cognitive assessment tool. Its primary function is to measure information processing speed and other cognitive abilities through a simple substitution task where users match symbols to numbers using a reference key. The app records crucial metrics such as symbols displayed, errors made, and the average time per selection to assess cognitive function.

This application has a range of important diagnostic applications. It is utilized to measure cognitive deterioration and even to help differentiate between brain-damaged in case of patients or tired workers.

From a technical standpoint, the SDMT app employs a Feature-First directory organization, which means its codebase is structured around specific functionalities. Key features include support for multiple languages, specifically English and Spanish, handled by its I10n module. The user interface is built around various Screens, such as Splash, Home, New Profile, Countdown, Test, and Results, guiding the user through the assessment process. The app manages

information flow between its different components using providers for State Management, covering aspects like test progress, keyboard input, time, symbols, test parameters, personal data, and device interactions. Additionally, a Utils module provides essential utilities for UI customization, standardized UI elements, and functions to handle the logic across different screens, as well as classes for saving internal test and user profile data.

For data handling, the SDMT app implements local device storage using Shared Preferences, ensuring that user profiles and test data persist even when the application is closed. Furthermore, it facilitates communication with a backend service through API endpoints, which are used for validating reference codes and submitting test results, indicating its integration into a broader data management system. More details can be found at <https://2025-upm-cognitive-test-dsdmt.readthedocs.io/en/latest/> while the source code can be found at [https://github.com/MultipleSclerosisMonitoring/2025 MEM CognitTest](https://github.com/MultipleSclerosisMonitoring/2025_MEM_CognitTest).

```
lib/
| +--- l10n/                # Localization system used for multilanguage
| | +---generated/         # Dart code that manages multilanguage
| | +---app_en.arb         # ARB file with all the text used in the app in English
| | +---app_es.arb        # ARB file with all the text used in the app in Spanish
| +---screens/            # Contains one file for every screen
| | +---countdownScreen.dart
| | +---homeScreen.dart
| | +---newProfileScreen.dart
| | +---resultsScreen.dart
| | +---splashScreen.dart
| | +---testScreen.dart
| +---state_management/   # Contains files for managing the communication between different w
| | +--locale_provider.dart # Only for the multilanguage feature
| | +--providers.dart      # All the providers used for state management
| +---utils/              # Utilities
| | +--constants.dart     # Constants used to parametrize numeric values in the app
| | +--HomeButton.dart    # Class created for the buttons in the home screen
| | +--numberKey.dart     # Class created for the numeric keyboard in the test screen
| | +--testFunctions.dart # Contains the functions that handle the logic in the test screen
| | +--homeFunctions.dart # Contains the functinos that handle the logic in the home and new
| | +--test.dart          # Class created to save internally information from the tests
| | +--profile.dart       # Class created to handle the data of the users profiles
| +---main.dart
```

Figure 10.- Project directory organization.

Figure 11 details a feature overview of the SDMT (Symbol Digit Modalities Test) application, showcasing a well-structured and modular design across five primary components: l10n, Screens, State_management, Utils, and Main. This breakdown suggests a strong emphasis on maintainability, scalability, and user experience.

The l10n component, which likely stands for localization, is responsible for managing the application's multi-language capabilities. Its sub-elements, "Generated," "English," and "Spanish," clearly indicate that the app supports at least two languages, with "Generated" possibly referring to automated processes for creating language files. This is crucial for reaching a broader user base and ensuring accessibility for diverse linguistic backgrounds.

The Screens component outlines the user interface flow, representing distinct views within the application. Starting with "Splash," which is typically a loading or introductory screen, the flow progresses to "Home," serving as the main navigation hub. "New profile" suggests user registration or profile creation. The "Countdown" screen precedes the "Test" screen, where the core cognitive assessment (Symbol Digit Modalities Test) takes place. Finally, "Results" indicates where test outcomes are displayed to the user. This sequence reflects a clear and intuitive user journey through the application.

State_management is a critical component for handling data and UI updates across the application. The presence of "Locale provider" indicates that language settings and other locale-

specific information are managed centrally, ensuring consistency across the app. "General providers" suggest a broader mechanism for sharing and updating information between different widgets and screens, which is fundamental for responsive and dynamic applications.

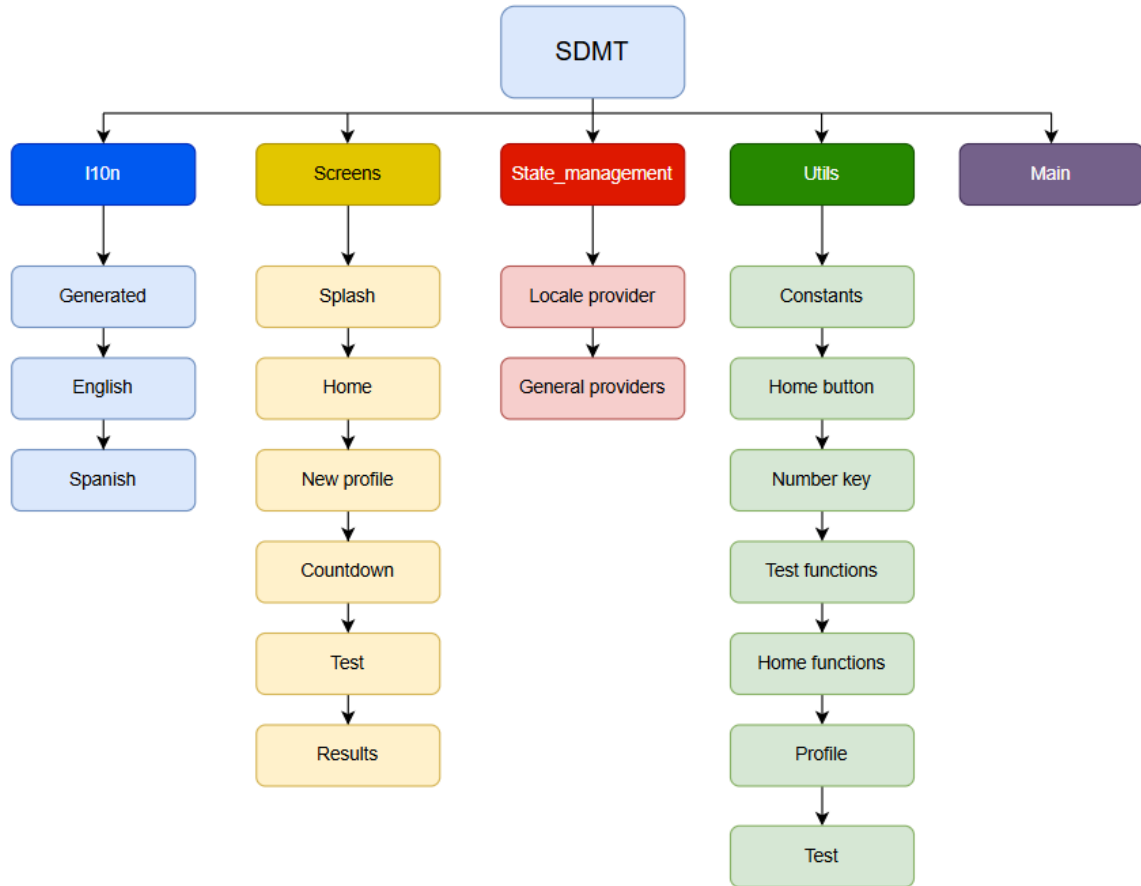


Figure 11.- Feature Overview.

The Utils component groups various utility functions and constants that support the application's core logic and UI. "Constants" are likely used for standardized values, such as UI modification parameters. "Home button" and "Number key" suggest standardized classes or functions for managing UI elements related to navigation and input. "Test functions," "Home functions," "Profile," and "Test" within

Utils point to helper functions and logic related to the respective screens, ensuring a clean separation of concerns and promoting code reusability. Additionally, this component includes classes for saving internal test and user profile data.

Finally, the Main component, though not detailed with sub-elements in this diagram, typically serves as the entry point of the application, orchestrating the initialization of all other components and setting up the overall application environment. This modular structure, with clear responsibilities assigned to each component, aligns with modern software development practices and contributes to the app's overall robustness and ease of development.

6 CONCLUSIONS

The report for Deliverable A1.D3.1, "Wearables and digital solutions for context enrichment in predictive models," comprehensively covers its expected outcomes by detailing the design

principles, methodological approach, and initial results pertaining to the integration of human-generated data into process models.

A key aspect of our methodology, informed by design science principles, has been the conceptualization of wearable data within a complex semantic framework. This is particularly critical for understanding the intricate interactions between discrete equipment states and human operators, ultimately striving to reduce discrepancies in comprehending the entire process flow. The proposed "HUMAN DATA FLOW" framework, with its emphasis on a Semantic Layer, is instrumental in connecting disparate data sources from physical layers, through a personal hub, and into various cloud platforms. This semantic connection, facilitated by ontologies, provides a structured and formalized representation of knowledge, enabling a common understanding of data across diverse systems and stakeholders. This is essential for integrating the heterogeneous data collected from wearables at the hub layer and processed through the cloud layers, preventing it from remaining a complex and manual task.

The report directly addresses the core requirement of "Design of mobile apps to collect information from different wearable devices for data collection". It explicitly states that "we have focused on the design of mobile applications to collect information from various wearable devices for data collection". This is further substantiated by the discussion of "HealthyWear," a mobile application developed with Flutter for cross-platform compatibility (Android and iOS). The architecture of HealthyWear is presented, showing its interaction with various wearable devices like smart socks, motion sensors, and smart bands, and how it leverages native BLE APIs for robust hardware access.

Regarding the requirement for "Collection of data from specific wearables such as pressure in feet (when the operator is walking), worker position, and heart rate (to check the relevance for stress levels)", the report elaborates on how HealthyWear consolidates data from "smart socks and motion sensors, with physiological metrics (e.g. heart rate, SpO2) from a smart band". It specifically mentions that "Smart socks provide plantar pressure, acceleration, angular velocity, and magnetic field data," while "wristbands supply heart rate and blood pressure". This directly aligns with collecting the specified types of data from operators.

The expected outcome that "The idea is not just to collect data in high frequency (depending on the variable) but to store them and be able to merge them with process data" is also thoroughly covered. The report highlights that "Sampling rates are high, ranging from 50 to 100 Hz, allowing for fine-grained movement analysis". It also describes a "synchronized buffering mechanism" to handle the high frequency and volume of data, tagging incoming packets with metadata for "robust multi-sensor data fusion and traceability". The data is then stored temporarily in "encrypted device memory" and uploaded to a cloud server using HTTPS, with an InfluxDB time series database selected for storage. This detailed data pipeline ensures that high-frequency data is collected, stored, and prepared for merging with other process data.

Finally, the critical requirement for "The interoperability of data expansions will be carefully addressed" is extensively discussed. The report emphasizes HealthyWear's "modular, hybrid architecture" which "combines cross-platform flexibility with optimized native performance". It explicitly states that "platform-dependent operations such as Bluetooth communication, sensor data handling, and file system access are implemented natively (Java on Android, Swift on iOS) and exposed to the Flutter framework via Method Channels". This hybrid strategy ensures that the app can "leverage the full capabilities of each platform without sacrificing code reuse or maintainability", which is crucial for achieving interoperability. The seamless data flow from wearable devices via Bluetooth to the mobile application, and then to a cloud server and Grafana dashboard for visualization, further demonstrates the achieved interoperability within the system. The use of standardized, structured formats for decoded data also supports interoperability.

Looking ahead, the robust semantic framework being developed for the human data flow is designed to seamlessly integrate with Subproject A1's WP4, which focuses on BIM (Building Information Modeling) and IoT integration. The detailed and contextually rich human behavioral

data, once semantically formalized, will provide an unprecedented layer of insight for the BIM models. This integration will allow for a dynamic understanding of how human actions and physiological states influence building asset performance and operational efficiency. For instance, semantically enriched gait analysis and other human physiological data can inform predictive maintenance strategies in BIM environments, optimize energy demand based on human presence and activity, and enhance overall asset management by linking human factors directly to the digital twin of the infrastructure. This synergistic approach, where human behavioral data enriches BIM and IoT systems through a sophisticated semantic layer, is poised to create a truly holistic and intelligent asset management ecosystem, aligning perfectly with the Industry 5.0 paradigm.

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