SmartWork: An IoT Enabled Unobtrusive Worker Health, Well-being and Functional Ability Monitoring Framework

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Abstract: Staying healthy in our workplaces is one of the most important priorities both for employers and employees, especially after the recent COVID-19 pandemic. Especially for older workers, that are more vulnerable, not only due to COVID-19 but also due to their chronic conditions that may be affecting their performance and productivity. This is more prevalent in western societies where populations are aging and people and governments start to consider staying at work longer to stay as active members of the society and live independently in better conditions. In this paper we present the SmartWork software suite that aims at building a worker-centric Internet of Things enabled system for workability sustainability, integrating unobtrusive sensing and modeling of the worker state with a suite of novel services for context and worker-aware adaptive work support. SmartWork is a ready to use, software suite tested in real-world installations that combines off-the-shelf and novel software and hardware components to provide workers with guidance on how to improve both their personal and professional lives.

1 INTRODUCTION

Governments and enterprises spend every year a lot of time, effort, and money to train and increase their workforce's abilities, knowledge, and expertise. Lifelong learning is the cornerstone of maintaining the best performance and highest productivity in any position either related to high-tech positions or not. If we include in this picture the aging of the worldwide population the cost of losing workers due to early retirement at a time where they have gathered all this knowledge and experience is extremely high. Such workers are of high value, if not in their original (on the field) positions, at least as consultants or trainers for younger workers, to facilitate the transfer of knowledge and expertise to the younger generations. Most advanced countries employ strategies to increase the presence of older employees in work environments and to reduce the early retirement rates and unemployment amongst older people. Especially within the European Union with the employment rate of 50-64-year-olds reaching only 66% as of 2020 (Commission, 2020) in the 27 member states.

A person can be characterized as an "older worker" in most cases due to physical changes associated with older ages that may have resulted in decreased performance in specific physical or mental activities, like the decline in vision or hearing, but this definition does not apply to everyone. Age-related conditions, such as the ones described above can start as early as the age of 50 (Liang et al., 2008). Similarly, chronic health conditions are more common in people aged over 50, especially in the western world, with almost 50% of the population suffering from hypertension, high cholesterol, heart disease, mental

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illness, diabetes, arthritis, back problems or asthma (Busse and Blümel, 2010) mainly due to the office worker lifestyles followed.

These workers may have diminished performance in physical activities but as we mentioned before their knowledge and experience give them an important value for their employers. Their younger colleagues can benefit from their help in experience-based tasks and duties (Ortet et al., 2019), thus, keeping these workers around can be of a huge benefit so that youngers can learn more pragmatically. It is then of paramount importance to provide workers with an age-friendly working and living environment through novel technologies such as the Internet of Things (IoT), body or wearable sensors, artificial intelligence (AI), and machine learning (ML). SmartWork (Kocsis et al., 2019; Amaxilatis et al., 2019) aims to build such an environment through the utilization of an IoT-enabled unobtrusive and ubiquitous sensor network that monitors the health and work conditions of workers at all times, provides suggestions for their performance and safety, and facilitates the knowledge and experience transfer between workers of different ages. We base our design on novel, scalable and viable architectures, and business models, using also the feedback from large-scale and multi-country pilot installations of the system under development.

The project created a Worker-Centric AI System for workability sustainability, integrating multiple sensing devices and modeling the worker's state with a suite of novel services for context and worker-aware adaptive work support. The unobtrusive and pervasive monitoring of the health, behavior, cognitive and emotional status of the worker enables the functional and cognitive decline risk assessment. To achieve these goals, our system is built upon existing reference architectures and well-defined practices especially in the domain of AAL. Basing our work on the Reference Architecture for open AAL platforms of universAAL (which has also been built on existing solutions from previous AAL projects, e.g., IN-LIFE) and by adopting extensions to support cloud-based solutions we can provide a robust, extensible, and privacy-respecting system. The SmartWork architecture takes advantage of all the interoperability features and capabilities of modern software and hardware solutions towards enabling the seamless integration of existing or developed web services, applications, and hardware solutions.

The rest of the paper is structured as follows: In Section 2 we showcase the SmartWork sensing network architecture. Section 3 provides more information on the sensing devices used, the applications developed and the data collected. In Section 4 we present the post-collection data processing and analytics capabilities of our system and in Section 5 we discuss how the whole system is tested in two real-world installations. Finally, in Section 7 we present our conclusions and take-away messages.

2 SYSTEM ARCHITECTURE

The SmartWork monitoring infrastructure is based on an unobtrusive IoT-based sensing infrastructure, either installed on the workers' workplace or worn by them, and a set of software applications installed on the computer of the workers and their mobile devices. Each device or application is responsible for measuring a set of characteristics of the workers' state and all the data are aggregated in the SmartWork cloud to generate more detailed insights. Using multiple devices and applications we can adapt our system based on the needs of each organization that uses it and extend or modify the set of devices used accordingly.

As discussed before, the worker data collection is done using both software and hardware. In more detail, in the current version of SmartWork we use the following components that will be described in more detail in the next section:

- Smart Mouse
- Withings Scale
- Focusbuddy
- ECG Vest
- Fitbit Activity Tracker
- Environmental Sensor Box

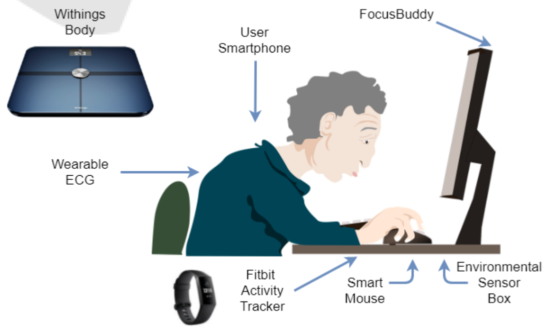

Figure 1: Flow of data in the SmartWork architecture.

Each of these devices collects data independently and communicates them to the SmartWork infrastructure for further processing and analysis. The flow of data collected is presented in Fig. 1. We can observe two main flows for the collected data. One is from the worker's computer directly to the SmartWork infrastructure while the second one uses the proprietary device's own infrastructure and APIs as an intermediate repository polled periodically by the SmartWork services to collect any available data. The second flow is something that cannot be avoided, as the devices do not offer any direct option to get data (e.g., the FitBit activity trackers), but shows how our implementation allows for easy integration of external sources.

Figure 2: Sensing components of the SmartWork suite.

To efficiently collect, store and process all time-series data from the IoT devices of the project, SmartWork uses internally the SparkWorks IoT Analytics Engine. It is designed to handle unlimited streams of data from multiple sources, volumes, and speeds, as well as multiple formats, convert them into a common format, and process them as needed by each use case. More details on the SparkWorks IoT Analytics Engine will be provided in Section 4. An appropriate RESTful application programming interface (API) is available for accessing the raw and processed data of the sensors as well as the metadata and user-related information.

Using all the collected data, developers of SmartWork are capable of creating useful applications for workers and employees in the following domains to build the SmartWork software suite:

- Unobtrusive Sensing at the workplace and on-the-move, and low-level heterogeneous data processing algorithms for efficient data transmission.
- A Ubiquitous Workplace, allowing for instant adaptation/personalization and seamless transfer between home and office environments (Vanderheiden et al., 2013).
- Modelling and Artificial Intelligence for risk assessment on multiple dimensions, related to the work ability of the employee.
- On-the-fly Flexibility and on-Demand Training (Leligou et al., 2019).
- Care Management and Interventions to deliver health and lifestyle self-management services to people with chronic conditions.

There are two basic entry points for the SmartWork users. The worker's smartphone and the worker's desktop computer. Three applications are available for both Android and iOS devices: (a) healthyMe mobile for connecting Fitbit and Withings accounts and displaying basic fitness-related feedback and (b) iCare for caretakers of the workers that need to monitor their health conditions or mental state and (c) Cardio real-time ECG recordings using the ECG Vest. On the desktop side the following applications are available for Windows 10 based computers:

- EnvSerial: for collecting data from the Environmental Sensor Box
- SmartMouse Suite: for collecting and processing data from the SmartMouse
- FocusBuddy: for collecting gaze tracking data from the installed webcam and assess worker's stress levels
- SmartWork desktop: for offering a central access point to all SmartWork services

Most of these applications follow the unobtrusive nature of the SmartWork sensing network, meaning that the user rarely needs to interact with them. EnvSerial, SmartMouse, and FocusBuddy are initially configured and operate in the background, while SmartWork desktop is there for users to inspect their collected data, access SmartWork services, receive notifications or suggestions to make their work environment better (e.g., increase their productivity or reduce their stress levels). All applications share the same login information, stored securely in the worker's computer (or smartphone) to further simplify access to the services.

3 SENSING COMPONENTS

In this section, we are going to provide a more detailed description of all the sensing components used in the SmartWork unobtrusive sensor network, the IoT devices and the applications used to collect their data.

3.1 Environmental Sensor Box

A USB-powered desktop sensor box is used in SmartWork to record the environmental conditions in the worker's office. The SensorBox is based on an extensible hardware design that is capable of measuring environmental conditions (temperature, relative humidity) and air quality levels, mainly Volatile Organic

Compounds that are the main pollutant in indoor environments.

The sensed data are collected by the EnvSerial application that is running on the worker's desktop application. The data are pre-processed and filtered by the application and then forwarded to the SmartWork infrastructure through a dedicated call in the data processing API. During the pre-processing, the application is also generating additional metrics like the thermal comfort estimate using the predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD) metrics (American Society of Heating and conditioning Engineers Inc., 2020). The flow of data from the Environmental Sensor Box devices through the EnvSerial application and SmartWork is described in Fig. 3

3.2 SmartMouse

The SmartMouse is an intelligent device that is capable of measuring several well-being parameters of the user unobtrusively, fusing the standard pointing module of a computer mouse with a combination of commercial and custom-developed sensors. All of the electronics of the device were encapsulated in a carefully developed custom design, having into consideration the feedback obtained from the target users while using the previous version of the device. This allowed us to create an ergonomic and comfortable device while providing maximum physical contact between the user and the array of sensors.

The pointing module of the intelligent mouse is doted with an RF and Bluetooth transceiver, allowing the device to be connected to different computers and exchange between them with a single button press. This approach was also extended to the sensing module, where the central processing unit (CPU) can commute between two different Bluetooth devices, based on the output provided by the pointing module. The CPU is responsible not only for the communication between the SmartMouse and the computer but also to interface with the wide range of onboard sensors present. This includes a Heart-Rate sensor (HR), an infra-red hand-temperature sensor, a custom-developed skin-conductance sensor with custom probes, and an inertial measurement unit (IMU) to evaluate hand movements. All of the sensors' raw data are filtered and processed locally. The generated information is then forwarded to also custom-developed mouse algorithms, which are responsible for outputting accurate measurements of the user's well-being indicators. All of the SmartMouses' units were fully tested using a custom procedure that uses robust and calibrated devices to evaluate all of the sensed parameters. This allowed us to fine-tune the architecture to improve sensing output, achieving high accuracy results.

On top of the mouse hardware and firmware developments, we have also created a software suite, targeted for Windows 10 system, that is installed on the user's computer to allow the communication between the machine and the sensing part of the end-device. The pointing functionality is assured by the embedded modules of the Operating System (OS). The SmartMouse software bundle is composed of three main components, described below:

- A Windows-based service that starts automatically without any external input when the user logs in on the computer. It is also responsible for implementing a custom Bluetooth profile to communicate with the end-device, calculating the high-level estimations about the emotional state of the user, and deploying a communication pipe with the SmartWork infrastructure. The data uplink between the mouse application and the server is assured by a RabbitMQ message queue directed to the SparkWorks IoT Analytics Engine, that processes the stream of data and stores it on the respective database.
- A graphical user interface (GUI), where the user can have a global vision of the data that is being generated by the mouse while having access to some configurations for the communication with the server and also for the application itself.
- A windows back-end application, responsible for tracking the cursor position on the screen and send the captured positions to the Windows-service via inter-process communication (IPC), to be fused with the remaining data and be fed to the emotional estimation algorithms.

The entire SmartMouse solution, which comprises both hardware, firmware, and software progress, was developed taking into account the evolution of technology and the outputs of the pretrials and trials performed, aiming for a solution that enhances the user's productivity and is comfortable and easy to use.

3.3 Web Camera

One of the predictive modules in SmartWork, FocusBuddy takes the user's gaze as well as other data as input and outputs continuous predictions on the user's cognitive state. For gaze tracking, we use Logitech C270. The software for tracking the user's eye point of gaze (EPOG), that is, the point in external space that the user's eyes are directed to, was built based on an open-source library that offers tracking of the

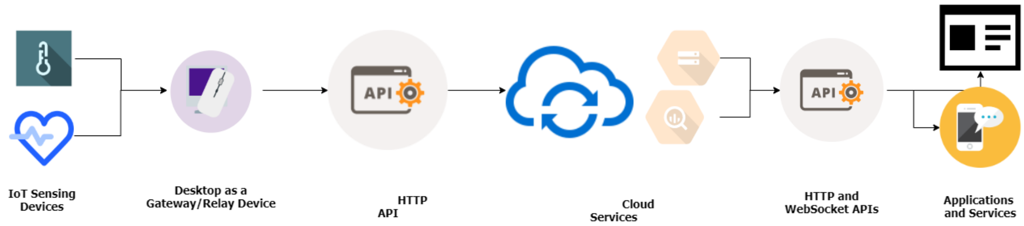

Figure 3: Flow of data from the PC connected IoT sensors and webcam to the SmartWork infrastructure.

user's eyes (iris) in a webcam image. The library relies on a pre-trained deep-learning model for face and eye detection. Pupil tracking is accomplished by determining the relative position of the iris within the eye.

On top of this library, we have developed a software for tracking the point were the user is looking on the computer screen based on the EPOG estimation [1]. This software determines gaze direction and maps this onto computer screen coordinates with the help of known calibration points. The viewer's distance from the screen can vary, which is compensated for by adjusting the calibration according to changes in apparent iris size. Estimated EPOG accuracy is around 400 pixels (3-4 cm), when viewing a 15-inch computer screen from 60 cm viewing distance. Changes in viewing distance are accommodated by observing corresponding changes in iris size.

3.3.1 FocusBuddy

FocusBuddy is an application that helps the user keep focus, while at the same time avoiding becoming fatigued, stressed, or overwhelmed by the work tasks. In more detail, FocusBuddy is a suite of software that runs on the user's computer, collecting and analyzing where the user looks on the screen, the user's heart rate, which window the user is interacting with, what mouse actions are performed. Machine learning, Long Short-Term Memory as a baseline model, is used to predict the user's cognitive state, namely stress level, mental fatigue, mental workload, and whether the user is focused or distracted. Internally, FocusBuddy consists of four submodules:

- A sensor part that runs directly on the desktop or laptop, collecting low-level information, such as the position of the currently active window, mouse actions, and so on.
- A locally hosted web app developed in Flutter that is tightly connected to the sensor part. It interacts with the user, collecting the users' input on how they feel at that particular time [2]. The web app is also responsible for presenting supporting advice to the users.
- A remotely hosted backend that produces predictions and handles the business logic of FocusBuddy.
- An AI-module, which implements data handling and model training.

The sensor part collects information in the background and periodically displays notifications (short-lived toasts) to the user. Initially, when run in bootstrap mode, the notifications take the user to a questionnaire for eliciting their perceived cognitive state. Subsequently, when run in prediction mode, the notifications display supportive advice based on the user's *predicted* cognitive state. While the Artificial Intelligence (AI) part is responsible for preparing (cleaning and normalizing) the collected data and training the user models, these models are made available for HTTP-requests by uploading them to the FocusBuddy backend server. Individual models are maintained for each user, using only their data. In this way, each user is served with a personalized model adapted to their work style and computer activity habits.

3.4 Fitness Trackers

The Fitbit Activity Trackers are be used in SmartWork and worn by the workers throughout the day to collect data about their physical activities. The API FitBit is periodically polled by the R2D2 service, developed by a project partner, and data is transferred from the Fitbit cloud services to R2D2 and then synced to the SmartWork Services. A similar approach is used to integrate other devices like the Withings Smart Scales, using the respective API for accessing worker's weight information. The use of the R2D2 service offers SmartWork an abstraction layer so that in the future we can integrate more activity trackers or other off-the-shelf devices that offer their proprietary API. Except for the physical activity data (step counts, heart rate, calories burned) the Fitbit activity trackers also provide us with sleep-related information, to get better estimates for the workers' quality of life. The flow of data from the Fitbit and Withings

[1]https://github.com/ritko/GazeTracking

[2]https://cseq.herokuapp.com/quest/

devices through R2D2 and SmartWork is described in Fig. 4

3.5 ECG Vest

The ECG Vest (Scirè et al., 2019; Akrivopoulos et al., 2019) is used by the SmartWork workers who are suffering from diagnosed chronic heart conditions to monitor the wearers in real-time when they are not feeling well. It provides information about the beats per minute, PQRS and RR intervals (Pingale, 2014) as well as a full ECG recording that can be used by cardiologists as an ECG Holter device recording. Based on that data received it is capable of sending notifications about the categorization of the beats observed when used in conjunction with an analysis algorithm on the wearer's smartphone and the Cardio application. The vest needs to be worn under the user's clothes as it needs direct contact with the skin for the electrodes to work properly. The vest collects the electrode data locally and transmits them to the user's smartphone although it is capable of performing part of the processing locally (e.g., beat-detection and RR interval calculation). The vest is powered by the new Nordic NRF52840 processor, using BLE5 for communication with the smartphone application. Additionally, the current design possesses additional sensing capabilities, like a 3 axis accelerometer, and can be extended to include sensors for body temperature or oxygen saturation sensors, that will help provide more data regarding the wearer and smarter monitoring based on the inputted data.

4 DATA PROCESSING

Data coming from devices are not always ready to be used from high-level applications. Further filtering, processing, or analysis is needed to extract better knowledge and information from it. Also, there are cases where data have gaps or erroneous values that are sent either from malfunctioning or misused devices. To eliminate such problems a data processing and aggregation layer is needed to do the hard work of extracted clean datasets from the raw data streams stemming out of the SmartWork unobtrusive sensor network. In our case, we use the SparkWorks IoT Analytics Engine to do all these operations as well as an API endpoint to serve and distribute all the resulting datasets to the SmartWork backend and end-user applications and services, and novel Data Imputation techniques to fill in any missing data in our datasets.

4.1 The SparkWorks IoT Analytics Engine

The SparkWorks IoT Analytics Engine (SparksIoT) is a cloud-based flexible and scalable IoT Data Analytics platform that can handle unbounded streams of data in near-real-time and distribute them to multiple applications and services as needed by each use case. The core of the engine is built using the powerful Apache Storm, the open-source distributed real-time computation system, that can reliable analyze any amount of data that will be generated by the SmartWork installations. All sensor data are fed to SparksIoT via two endpoints: (1) an AMQP[3] connection (using RabbitMQ[4]) and (2) a Restful HTTPS API for applications that cannot use the AMQP connection. The Monitoring Controller is receiving data from both endpoints and is responsible for filtering any wrong data coming from the sensors before submitting them in the core engine. The core engine is composed of multiple micro-services that sequentially perform the analytics operations on the streams of data received until the processed data are stored in their final form in the data storage micro-service. In more detail, the core engine contains the following services:

- Streaming Data Annotation Service
- Streaming Data Filtering Service
- Streaming Data Analytics Service
- Data Storage Service
- Data API Service

Figure 5 shows a graphical representation of the services listed above and their main interactions. We need to note here that although some arrows appear to connect services directly, in most cases this happens through the AMQP message broker, in the same way, that sensors submit data to the system, mainly in the cases where streaming sensor data are exchanged. The only case where services are communicating directly is the retrieval of historical data by the Data API from the Storage Service, where the API server directly queries the internal Storage Service API. In the next subsections, we are presenting the operation of all services of the SparksIoT engine.

4.1.1 Streaming Data Annotation Service

This service is responsible for two main tasks. The first task is to check the validity of the origin of the data, making sure that each user is providing data in the appropriate format and that the data provided refer

[3]https://www.amqp.org/
[4]https://www.rabbitmq.com/

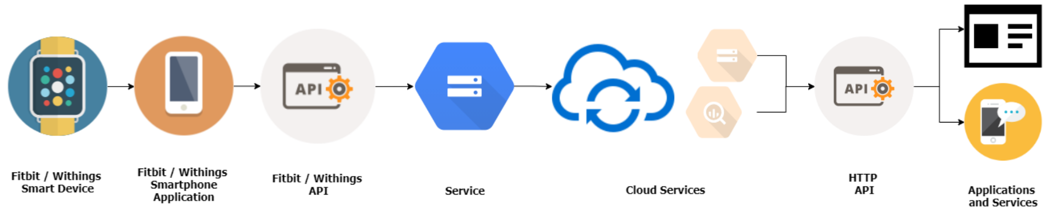

Figure 4: Flow of data from the R2D2 connected trackers to the SmartWork infrastructure.

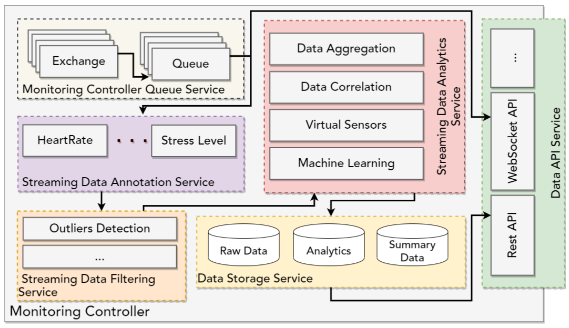

Figure 5: The SparksIoT core engine services.

to the correct user. The second and more important task is to extract from the metadata provided by the sender what these data describe. Each sensor measurement sent to the platform should contain at least 3 parameters. The systemName, the value and the timestamp of the measurement. The systemName is a text-based identifier that contains information about the owner of the data, and the type of data described in a URI format[5]. The timestamp value is expressed in Unix time (milliseconds since 1/1/1970) and the value is a simple numerical representation of the sensor's received data. Based on the sensor data received, the Streaming Data Annotation Service is capable of generating the correct metadata and attaching them to the sensor data object. Such data are the observed phenomenon and the unit of measurement used to express it. For example, for a heart-rate measurement the observed phenomenon would be *Heart Rate* and the unit of measurement, *Beats Per Minute*. These data need to be predefined for the platform so that the annotation can be successful, and as a result, a set of regular expressions that describe each systemName pattern needs to be unique so that no annotations overlap. The generated metadata along with the sensor data are sent back to the Queue Service for further analysis and storage.

4.1.2 Streaming Data Filtering Service

This service is responsible for checking the data received for abnormal values and error data that may have eluded any filtering in the lower levels. It can use both the historical data of the sensor (based on its systemName) and the metadata generated in the previous step to do the desired filtering. The actual implementation of the filtering is based on the business logic of the application developed and the requirements set up for this observed phenomenon with multiple algorithms (e.g., Standard Deviation or IQR Outliers).

4.1.3 Streaming Data Analytics Service

The Analytics Service operation on the streams of data resulting from the Filtering Service and generates time-based analytics and aggregations on the sensor data observed. It is capable of generating different types of analytics based on the observed parameter and analytics on multiple time granularities based on the requirements of the project. Typically, it calculates the average values of the received sensor data on time intervals like 5 minutes, 60 minutes 1 day, and 1 month based on requirements observed from previous projects. The service is built around the well-established data analytics framework, Apache Storm.

4.1.4 Data Storage Service

The Data Storage Service is responsible for receiving unprocessed and processed data from the AMQP broker and store them in three separate databases. The first one is a Redis[6] store, used to store the latest values from the sensors, and the latest results from the processing for each time interval. The second store is responsible for storing all raw data of the sensors. It is built using MongoDB[7] for high scalability and performance. The third store is storing all aggregated and processed data, for each time interval, as the results from the processing engine.

4.1.5 Data API Service

The Data API Service is built using Spring Boot[8] to offer highly scalable endpoints for all the operations of the resulting system.

[5] https://en.wikipedia.org/wiki/Uniform_Resource_Identifier

[6] https://redis.io/

[7] https://www.mongodb.com/

[8] https://spring.io/projects/spring-boot

4.2 Data Imputation

The ubiquitous sensing system of the SmartWork platform relentlessly collects data coming from heterogeneous sources in terms of sensing device or sampling rate. This uninterrupted collection is often accompanied by missing entries, yielding the need for estimating these missing values through imputation, which may prove unnecessary or computationally expensive in relation to the outcome. The data imputation module mainly consists of two sub-modules:

- the Data Quality Assessment module
- the module performing the imputation itself

The former module implements a data quality assessment approach that allows for decision-making regarding the need/efficiency of data completion to save system computational resources and ensure the quality of the imputed data if imputation is worth being performed. The introduced algorithm is adapted and targeted at the singularities of the data completion paradigm and does not attempt to evaluate the data quality of a data stream as an entity.

Data imputation methods in a multi-channel data setting are split into two categories:

- Single-channel imputation approaches, performing imputation on each data channel individually
- Multi-channel imputation approaches, performing imputation on all channels simultaneously, additionally leveraging the inter-correlation observed between different channels

In compliance with this segregation, the Data Quality Assessment module provides a score for both the single-channel imputation case, yielding a total score as the sum of the scores of the individual data channels quality scores and the multi-channel imputation case. In the former paradigm, the data quality score for individual channels is calculated by quantifying the dependence of the score on the percentage of missing values detected in a given temporal sequence of data and the maximum number of consecutive missing values observed in the time series. In the multi-channel paradigm, the score is additionally dependent upon the correlations of each data channel with the two highest correlated data channels of the rest of the channels.

After having conducted experiments on a variety of missing data settings, across different data missingness patterns (Data Missing Completely at Random, Missing Blocks of data(at random), Mixed types of Missingness (containing instances of both the former two categories)), it was decided that the most appropriate technique for simultaneously maximizing the accuracy of the performed imputation as well as minimizing the computation load demanded and, subsequently, minimizing the computational time to facilitate real-time analysis and optimized storage, was the Miss Forest algorithm (Stekhoven and Bühlmann, 2011). Thus, the currently employed approach by default in the Data Imputation module is an iterative imputation method based on a random forest that tries to constitute a multiple imputation scheme through averaging over numerous unpruned classification or regression trees. Multi-channel data imputation schemes allow for the performance of data completion while capturing the temporal correlations between quantities that are related among themselves, such as heart rate and steps made time-series, which are commonly expected to be highly correlated. MissForest was found to introduce the most attractive trade-off between computational expense and imputation accuracy or, otherwise, reconstruction error.

The missForest implementation exploited for fulfilling SmartWork's goals was an R package. Subsequently, the method was prototyped using Python 3.7 and missingpy[9], a library for missing data imputation which provides an API consistent with sci-kit learn.

5 REAL WORLD EVALUATION

The design and implementation of age-appropriate living and working environments is a major challenge as the proportion of older citizens, who are active members of society and want to continue to live actively and independently, is constantly increasing.

Intending to achieve more appropriate and effective results, SmartWork strives for the active involvement of its end-users (office workers over 55 years of age, their informal managers, and caregivers) in the co-creation and subsequent evaluation of the system, through the implementation of 2 pilots (Portugal and Denmark).

In each of these target groups, it is intended to produce specific benefits:

- Office workers (55+) - through continuous monitoring and assessment of their functional and cognitive capacity, as well as the risk of deterioration of their health status, and the consequent provision of tailored support to work.
- Employers - through their capacity to generate greater productivity and efficiency in office staff, using intelligent tools to support decision-making and contextual knowledge management.

[9]https://pypi.org/project/missingpy

- Caregivers / Family Members - by monitoring the general health status of the people they care for, providing them with complementary support for informal care tasks.

Hence, the need to setup an adequate study protocol that clearly includes the study objectives, the methods, the procedures and the instruments used for data collection, the administrative aspects of the study, and bibliographic references.

5.1 Setting up the Evaluation Framework

The evaluation framework was set up in several stages. This was done to allow peer-revision with end-user organizations and collect the opinions from the Ethical Committee and Data Protection Officers (DPOs) of each involved organization.

Overall, we started by preparing an extensive document formulating the ”Pilot Study Protocol”, which already anticipated the two phases of testing. The structure of such document follows our reference model, as adopted for similar project and evaluation works. It includes mainly:

1. Objectives
   (a) Primary objectives
   (b) Secondary objectives
2. Study design
   (a) Setting
   (b) Recruitment process
      i. General Inclusion Criteria
      ii. General Exclusion Criteria
      iii. Sample size
      iv. Groups structure and Randomization of participants
      v. Anonimisation procedures
      vi. Mobilisation and information provided to participants
   (c) Research design
      i. Hypothesis
      ii. Overall methodology
      iii. Overall effectiveness
   (d) Digital tools and devices
   (e) Instruments and Metrics
   (f) Risks for participants
   (g) Privacy Protection Plan
   (h) Administrative aspects of the study

After completion, this documentation was submitted to both the Ethical Committee and DPOs. Upon positive opinions, we were in the conditions to initiate the evaluation research work. The evaluation covered essentially two aspects. One related to ”Usability and UX evaluation” and the second related to ”Workflow, impact and overall effectiveness”.

5.2 Usability and UX Evaluation

The main objective of this evaluation is to assess the parameters of the user interface, user experience, and overall usability of the system. The empirical usability assessment is based on a multi-method approach that assesses: 1) self-perceived usability, 2) usability reported by the evaluator, and 3) performance evaluation. For self-perceived usability assessment, i.e. considering the users' opinion, and for the evaluation based on the evaluator's opinion on the participant's performance, validated usability assessment tools will be used. Quantitative data on users' performance in specific tasks will be recorded in log files (from each digital tool used) to record the success or failure of tasks, duration (in seconds), and the total number of errors. In this type of multi-method evaluation, the qualitative results of the usability evaluation (positive aspects and negative -barriers aspects of technology) are enhanced and complemented with quantitative results enabling a more accurate assessment, while avoiding overloading end users with long and repetitive questionnaires for the usability evaluation. The participants in the usability studies will be the older workers and employers that will work directly with SmartWork. There will be two moments of usability assessment. One, in the baseline, in the first contact with SmartWork technology to evaluate the first impression that users get of the system. Since participants at this stage have no knowledge or experience with SmartWork, they should follow a predefined sequence of steps (e.g., tutorial) to walk through the main system features and give an opinion on them. The second moment of usability evaluation should take place after 8 weeks when participants already have experience and mastery in using the technology. At this stage, there is no fixed sequence of steps in using the system, and the evaluation is made after regular use of SmartWork.

5.3 Workflow, Impact and Overall Effectiveness

The main objective of this evaluation is to analyze the utility and impact of SmartWork in its users' lives. The focus will be on the workflow of the workers, employers, and caregivers when handling activities that are influenced by using SmartWork and should occur after some period of using the system (months 2, 4, 6).

Four focus groups will be held with the different users of SmartWork (older workers, employers, and caregivers/ family members). A Focus group is a qualitative data collection technique, highly popular in several contexts, which brings together a small number of people and promotes informal discussion on a specific topic. This method aims to extract participant's perceptions, feelings, attitudes, and ideas about a particular subject. One researcher should assume the moderator role, being responsible for introducing the topics, promoting participation and maintaining the discussion.

5.4 Instruments and Metrics

In SmartWork's evaluation framework the majority of instruments and metrics used to assess the overall system were adopted from commonly accepted and validated measurement instruments and metrics. The following list describes each of the instruments used, after carefully selected and ensured their validity in the different languages used at each pilot site.

- Sociodemographic Questionnaire (self-included in the WHOQOL-BREF)
- Quality of Life (QoL) - WHOQOL-BREF
- Work Ability Index (WAI)
- Short-Form Health Survey 36 Item v2 (SF-36v2)
- The Copenhagen Psychosocial Questionnaire II - COPSOQII
- Fatigue Impact Scale v2 (FISv2)
- Older Americans Resources and Services Multidimensional Functional Assessment Questionnaire (OARS)
- Pittsburg Sleep Quality Index (PSQI)
- Overall Satisfaction Rating Question
- System Usability Scale (SUS)

6 PRELIMINARY RESULTS AND DISCUSSION

Considering all previously described and considering we conducted the initial phase of evaluation, we can present our preliminary results on SmartWork's evaluation. The initial phase was conducted at one of the pilot sites and had a total duration of 3 months.

Sociodemographic Questionnaire. Based on the information collected through the sociodemographic questionnaire applied to 10 participants at the baseline stage, we characterize our target population as follows:

- age range of 55 to 72 years old (with a larger frequency in the age range between 55 and 60 years old – 50%).
- most of the participants were women (70%), married (80%) and concluded the upper secondary level of education (60%).
- half of the sample worked as Social Educator (50%), either with children or with older adults.

SUS: System Usability Scale. When comparing the score results from both baseline and final assessments for this stage (in a 1 to 100 range), we understand that:

- there was an expressive growth related to the final rate attributed by older workers to the SmartWork system (with 30% more rating it over 68).
- on the opposite, there was a 20% increase in the final scoring below 50.

Such a result may suggest that participants found the first version of SmartWork acceptable in terms of usability, but users' expectations were not fully accomplished at this stage, stressing the need to proceed to further improvements in the final prototype.

Individual Interviews. Overall, participant's satisfaction with the SmartWork services and functionalities, from the midterm to the final interview, seems to significantly increased. This is supported attending to the proportion of participants that referred "to be pleased", as we observed 30% more ratings between "7", "8" and "9". Their final improvement suggestions were, therefore, mainly related to:

- Having more direct support from the project team, through the whole trial operation;
- The adoption of a lay language, duly translated and easily understandable for the user;
- The FitBit bulkiness, tightness (in some cases of larger fists) and uncomfortable to sleep with;
- The possibility of having the system installed on their personal phones, not in a different one;
- The ability of directly accessing their own behavior monitoring at work, through a dashboard;
- Their interest in a service that allowed to organize work better, regarding time spent at each task.

7 CONCLUSIONS

In this work, we presented the design of the SmartWork worker-centric IoT enabled ubiquitous work monitoring system. A suite of novel services to provide the means for workability sustainability for the older office workers. The whole system was tested in real-world environments during a three-month trial period with 10 participants showcasing the usefulness of the system and the potential impact it could have on their everyday lives. The whole system is currently tested on a much larger scale to further investigate its usability and scalability to help larger worker groups.

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