D4.1 - Definition of the indicators and metrics

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Short Abstract

This report contains the description of the metrics and indicators used by the Decision Support System (DSS) for recommending and stimulating the user during the use of the NESTORE coaching system used to make healthier lifestyle choices. This document collects the outcomes of Task 4.1 – Algorithms for Short-term post-processing and extraction of indicators, whose objective is to extract knowledge from data streams generated by the NESTORE sensors and software applications. This kind of data are continuously mined to extract indicators about the NESTORE target domains identified in the WP2 activities, namely physiological, nutritional, cognitive and mental status and social behaviour of the user.

Key Words

Indicators; Metrics; Decision Support System; Physiological indicators; Nutritional indicators; Cognitive and Mental Status and Social Behaviour indicators.

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1 Introduction

The main aim of Work Package 4 activities is to build a technology and intelligence infrastructure able to provide decision support to prevent the decline in the well-being of older people. The five domains of well-being identified in NESTORE are physical, mental, cognitive, social, and nutritional. With this aim, a Decision Support System (DSS) is designed to provide both real-time suggestions and long-term recommendations by recognizing user habits based on data gathered by the system as described in D3.1 and D3.2 documents.

The DSS bases its online recommendations on a dynamic model mainly constructed on the knowledge extracted from sensed data within the NESTORE domains. Scope of this document is to collect the outcome of Task 4.1 – "Algorithms for Short-term post-processing and extraction of indicators", that provides the data/information needed to construct the dynamic model used by the DSS. The resulting framework described in this document includes dynamic and online algorithms for data cleaning, data analysis. mapping, manual and semi-automatic categorization.

1.1 Motivation and rationale

After analysing Personas and complementing the information with domain experts, as described in document D4.3.1 and to be further detailed in D4.3.2, it is proposed a two-fold user profile used by the DSS to provide recommendations:

- *Static profile*. It is formed by the status and preferences of the user and it is characterized by containing non-varying attributes. Concretely it includes demographic characteristics, attributes regarding the context where the user lives, physical and physiological aspects and baseline data of the various domains.
- *Dynamic profile.* It is built dynamically while receiving data from sensors, software applications and contextual APIs. It is foreseen to receive daily indicators about the different domains and also contextual information.

The static profiling has been already described in D4.3.1 and it is the process of analysing a user's static and predictable characteristics. User static profile features include factual data, such as the idiosyncrasy of their residence (e.g. do they live in a rural or in an urban area?), or their diet routines (e.g. is meat part of their diet?), as well as inter-individual differences in the other NESTORE domains (marital status and perceptions of loneliness, cognitive functionality, physical fitness, etc.). They also describe the environment and living context of users.

Dynamic profiling is the process of analysing data coming at run-time from the sensors and applications deployed in the NESTORE user's ecosystem. It describes the changing context of the user, which is the element that leads the personalisation process. The information used to construct the dynamic profile of the user is described in detail in this document. We call this kind of information *indicator*.

The dynamic profile also includes parts of knowledge provided by the outcomes of Task 4.2 – "Algorithms for Recognition of trends and user habits". Trends and patterns in the five NESTORE well-being domains are extracted from daily indicators gathered in Task 4.1. This analysis provides a further level of understanding of the global status of the end-user. For this reason, in this document, we will also refer to long-term indicators and metrics, when needed.

The document is structured as follows. In Section 2, we illustrate the methodological approach used to identify the indicators that feed the DSS, also providing a definition for each of the relevant categories. Section 3 describes the data processing framework. Section 4 represents the core contribution of this deliverable and details all the chosen indicators and metrics for each domain. Finally, three appendices are attached, in which implementations details and preliminary results are provided, together with the complete list of the indicators and their main characteristics.

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1.2 Relation with other workpackages

From a general Work Package 4 perspective, the DSS is designed to provide both real-time suggestions and long-term recommendations by recognizing habits based on data gathered from the monitoring system developed in the Work Package 3. The recommendations will be delivered and integrated, in the form of coaching plans, and consumed by the virtual coach implemented in the Work Package 5 activities. The DSS will receive as main input data from environmental sensors and wearables as well as mental and social status. To perform a more effective profiling, contextual data is also taken into account. For doing so, a technological model based on outputs of WP2 is built and complemented by biomarkers and other indicators (i.e. social interaction).

From the perspective of Task 4.1 and, partially, Task 4.2 activities, data coming from Work Package 3 will be mainly streams of data. One of the main objectives of Task 4.1, and consequently Task 4.2, is to extract knowledge from these streams to both facilitate the subsequent decision making and adapt the general model to infer valuable information. These data are continuously mined to extract the indicators of the five domains defined and structured in Work Package 2. To this end, information coming from the sensing infrastructure, provided by Work Package 3, is post-processed to fit the Work Package 2 models. The processing tasks will run on the Work Package 6 software infrastructure using the developed interface to access and send data. Some inputs-to and outcomes-from the activities of Task 4.1 and Task 4.2 are directly retrieved and given back to the user through a chatbot developed in Work Package 5, while the main output will be used to feed the DSS developed in Task 4.3 and Task 4.4.

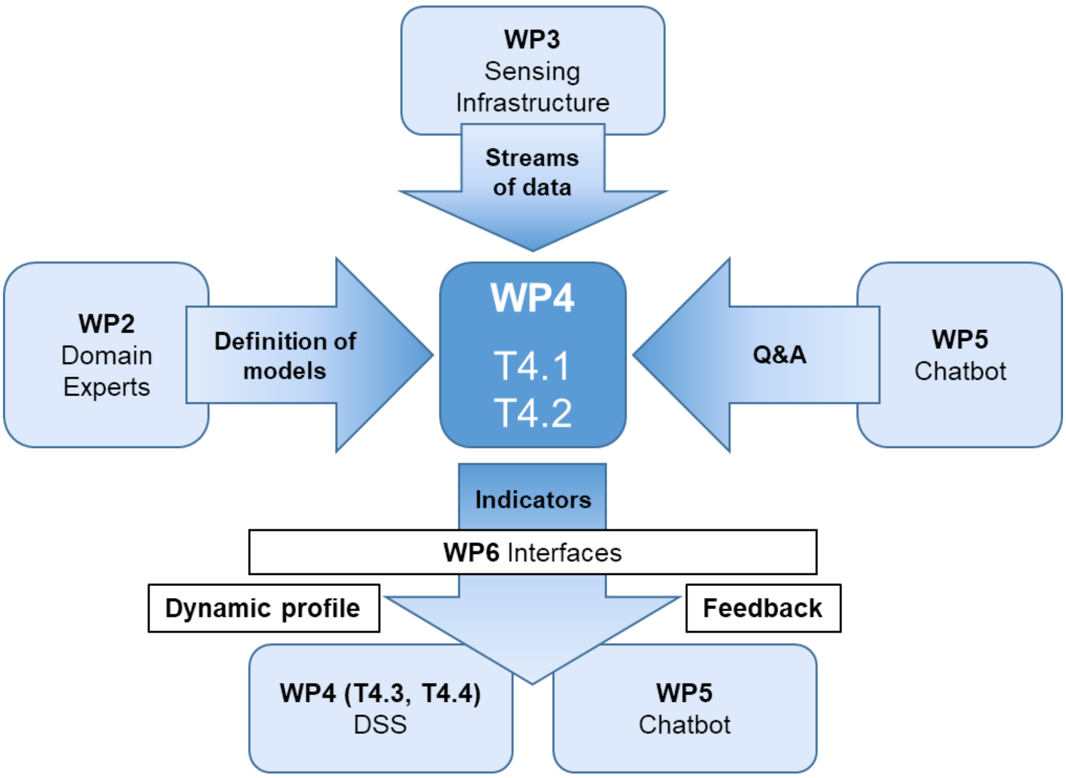

Figure 1 Graphical representation of the relationships among WP4 – T4.1 & T4.2, the activities of other NESTORE work packages, and the activities of other WP4 tasks

Figure 1 shows a graphical representation of the relationships among Work Package 4 – Task 4.1 and 4.2, the activities of other NESTORE work packages, and the activities of the other internal tasks of Work Package 4.

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2 Methodological approach to the definition of indicators and metrics

The models provided by the domain experts resulting from Work Package 2 activities aim to investigate, define and structure the target user's behaviour. This is achieved through literature analysis and knowledge provided by the partners, so as to obtain the complete set of parameters needed to characterize the subject status and behaviour in each well-being domain together with relevant variation. The specific parameters coming from the analysis performed in Tasks 2.1, 2.2, and 2.3 for each domain have been aggregated to provide a holistic view of the person. This is to better tune both the system response and the rules provided to the end-user in terms of virtual coaching.

By design, this holistic view (document D2.1 and Annexes) covers all the possible variables that characterize the target user, without considering availability of sensors, possible unobtrusiveness of the resulting system, and user experience. For this reason, the complete list of variables provided in the document D2.1 has been refined in order to also match the requirements coming from the co-design activities in terms of unobtrusiveness of the NESTORE system and the sensor selection, in terms of availability of technologies, performed in the Work Package 3 activities.

The resulting variables have been identified as useful by the experts to be continuously monitored during the use of the NESTORE system. We denote these variables *indicators*.

We have different indicators in each of the five NESTORE domains and they are computed in different ways and along different time frames. We define the mathematical function or algorithm that associates a quantifiable number to the indicator or a set of them as a *metric* (e.g., average over a predefined number of indicator's instances in a period).

The NESTORE DSS is based on a three-layer structure: i) a short-term analysis that analyses data on a daily basis; ii) a long-term analysis that looks at trends and is able to detect change and adapts the coach in the long term, following the changing needs of people as they age; iii) a combined short- and long-term analysis to provide a personalized mix of activities for finally sending personalized plans to the Virtual Coach when appropriate.

We also reflect this structure in the definition of indicators, with respect to time. The chosen indicators can be:

- *Short-term indicators*: Knowledge extracted from daily sensed data. This allows the system to detect specific time-limited activities (e.g., during physical or cognitive exercises), or the general status of the user during his daily life;

- *Long-term indicators*: Long-term behaviour is the sum of short-term behaviour assessments of the NESTORE system that captures the general trend over a prolonged period . This allows the system to infer user habits, daily life activities and other preferences.

Some of the indicators, according to the required metric, can be both short- and long-term indicators. All the details for each indicator are provided in the related following sections.

For ease of use, the complete list of chosen indicators for each domain, together with their nature (short-/long-term) and the kind of data source used to infer them are shown in Appendix 1.

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3 Data processing framework

In this section, we give insights on the general architecture of the data processing framework in charge of extracting indicators for each domain. Each domain has a specific NESTORE module that runs on top of a message queue, intercepting messages related to its field of action (sensed data sent through specific buses, please refer to document D6.3.1 for additional technical details). Data processing modules that intercept events coming from sensors and applications are deployed on the NESTORE Cloud infrastructure, developed in Work Package 6 activities. Some data processing modules pre-elaborate data on board of the specific device (e.g., wearable device, sleep quality sensor, etc.) and then send indicators to the cloud in a Web of Things (WoT) approach (more details in document D3.1.1 and D3.2.1) ready to be used by long-term data processing modules.

Figure 2 shows a deployment diagram with the modules related to Task 4.1 and 4.2 activities highlighted in a red box.

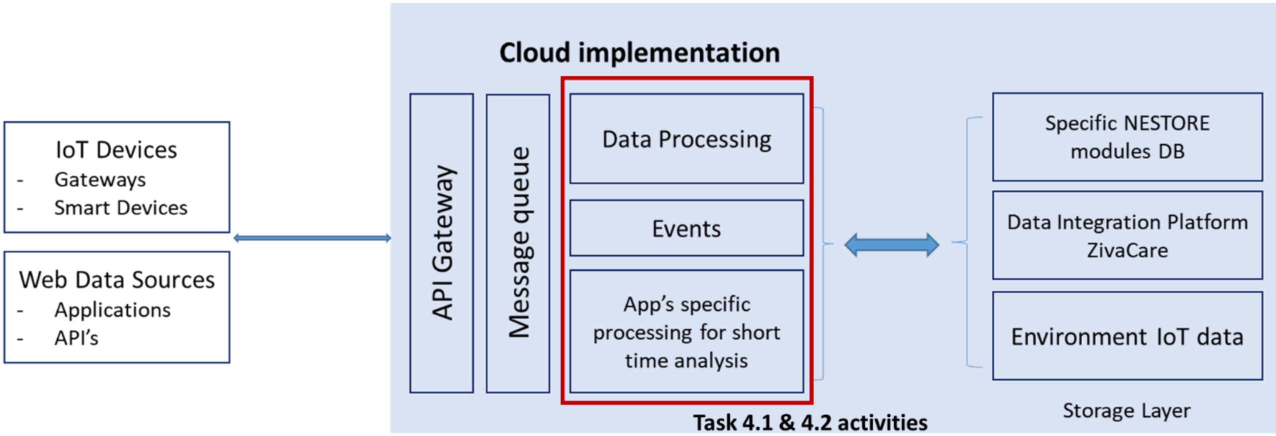

Figure 2 The data processing framework running on the NESTORE cloud infrastructure

As we can see in Figure 2, we have different sources of information. We differentiate all the possible source of data in two main categories: *hard* and *soft* data.

In the Work Package 3 realm, we call *environmental* device any sensor deployed in the user's vital space, while *wearable* the device worn by the user during his daily activities. We call the information coming from these kind of physical devices *hard data*.

As further source of information about the user's status, we can have derived data as result of computation or fusing strategy, data coming from web data sources, like applications and third parties APIs, and data coming from a direct input of the user, as questionnaires administered to the user through the NESTORE chatbot. We call this latter source of information *soft* data.

Once the indicators are extracted, they become available to be used by the DSS in its data flow for recommending coaching plans, based on the personalised dynamic profile of the user. Figure 3 shows how the dynamic profile, built using the extracted indicators described in this document, is used by the DSS to provide recommendations. More details can be found in the preliminary document D4.3.1, while an in depth view will be given in the final version (D4.3.2) of document D4.3.

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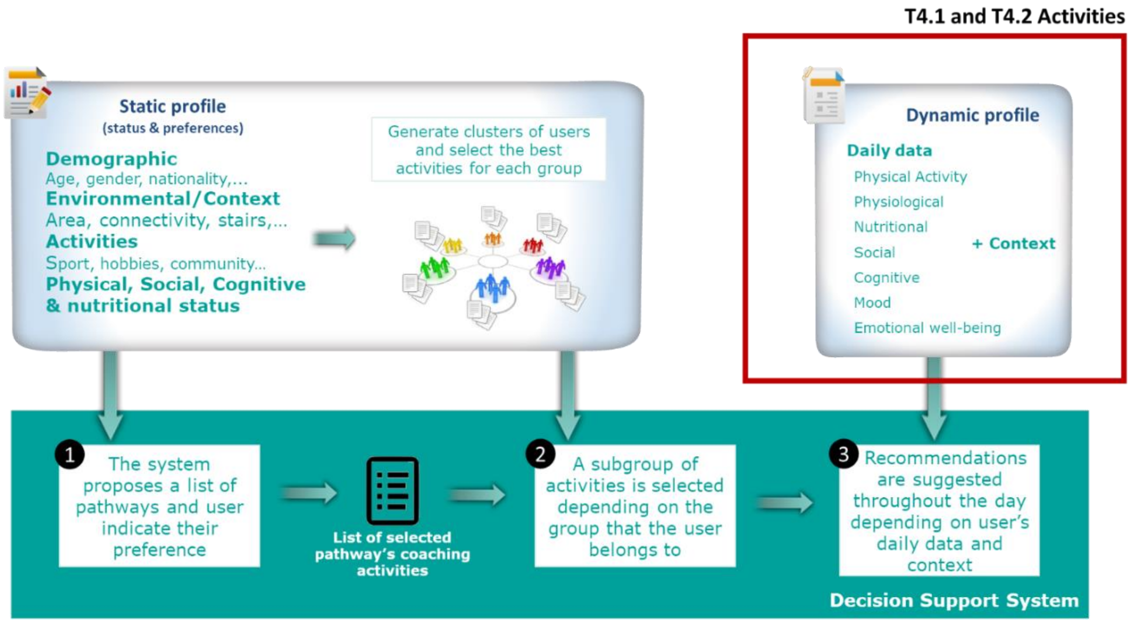

Figure 3 Data flow for recommending coaching plans, the indicators described in this document are used to build the dynamic profile

During the period of Task 4.1 and 4.2 activities, the actual development of software modules has been managed and tracked by means of a dedicated online spread sheet available at the following link: https://docs.google.com/spreadsheets/d/1a_Hwu2dKrlXuXKen4h-XNi75wUfvYXQ8TWc_U3JWsR8/edit?usp=sharing
Figure 4 shows a screenshot of the management and tracking web page, in which the domain, output of the computation, a short description, the used input variables, and the short-/long-term nature of the indicators are reported. The spreadsheet was also intended to track the status of the actual development of the processing algorithms with the indication of the domain and technical expert together with the relative schedule.

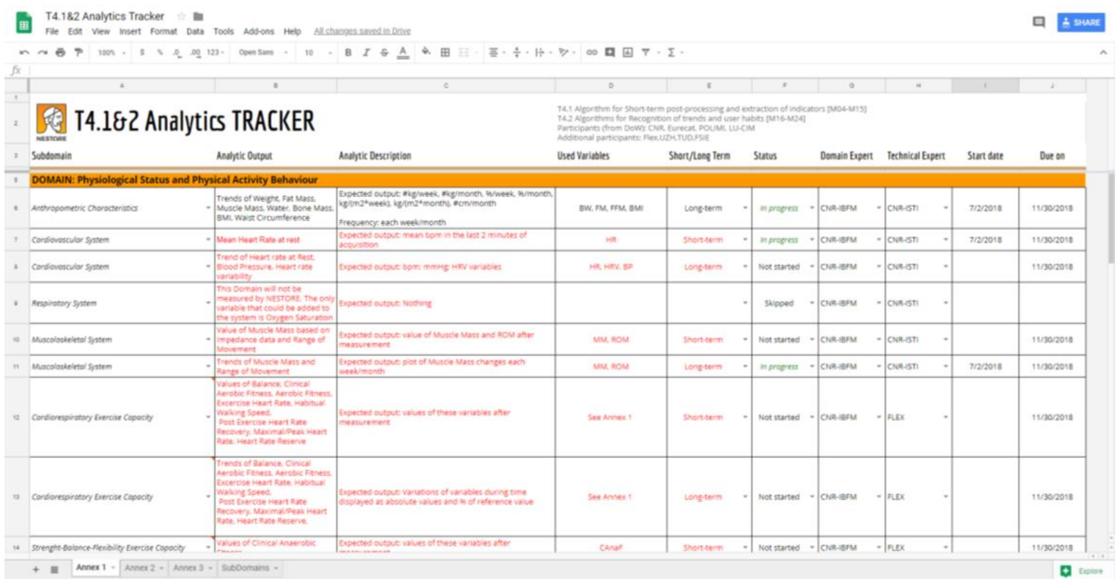

Figure 4 The spread sheet used to track the actual development of the software modules

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4 Data processing and indicators extraction

In this Section, we describe for each domain the chosen indicators and how we extract them from the hard/soft data sensed during the NESTORE pilots.

4.1 Physiological Status and Physical Activity Behaviour

The indicators presented in the following chapter derive from the Physiological Status and Physical Activity Behaviour section of the deliverable D2.1. These indicators have been selected following the indications provided by the domain experts and considering the actual activities that a Nestore user will perform during the pilot.

In this context, we define two types of user's daily living physical activities to be monitored during the NESTORE piloting: non-structured and structured activities. Free living non-structured activities represent any kind of physical activity taken during the day (i.e., walking for transport, housework, generic daily living activities). Conversely, structured activities are defined as planned, structured, repetitive, and/or purposeful physical activities suggested by the coaching system and aimed to improve or maintain one or more components of the physical fitness of the user.

We call the indicators related to non-structured "user daily living indicators", while indicators related to structured activities are called "coaching exercise indicators". Please note that all activities not suggested by the Nestore coach are dealt as non-structured activities. In order to manage a structured activity, the wearable device receive as input from the coach the type of activity, the activity target intensity, and the activity target duration (defined in the following). If the activity type is different from the ones expected (e.g. gym training), the coach informs the wearable device that the user is going to perform a *generic cardio activity*.

4.1.1 User daily living indicators

This section describes in details the indicators for non-structured activities chosen following the indications provided by the domain experts.

4.1.1.1 User general indicators

These indicators represent the overall physiological status of the user. They are computed at baseline (MHR) or on short-term (RHR) and long-term (MSL) base.

- *Maximal Heart Rate* (*MHR*): theoretical Maximal Heart Rate of the NESTORE user. It can be estimated knowing some user characteristics (e.g. the simplest formula: Maximal Heart Rate [bpm] = 208 – (0.7 x User Age). It should be computed in the cloud and provided to the wearable.
- *Resting Heart Rate* (*RHR*): it represents the User Heart Rate in resting condition. It should be monitored as soon as the user wakes up.
- *Medium Step Length* (*MSL*): it is the medium step length of the user reported both for walking and for running activities.

4.1.1.2 Anthropometric characteristics

Considering the subdomains and related variables described in Deliverable D2.1 and the indicators chosen as described in Section 3, the Fat Mass (FM), Total Body Water (TBW), Muscle Mass (MS), Bone Mass (BM) and Body Mass Index (BMI) are directly evaluated and collected through the Smart Scale provided by Withings company. The scale uses the Bioelectrical Impedance Analysis (BIA) method. It sends a tiny current allowing us to measure users' impedance which can then be used to calculate an estimated TBW. This method presents a high sensitivity about the user hydration level. The indicators percentage could vary widely from day to day based on how much water the user drank.
TBW can be used to estimate fat-free body mass and, by difference with body weight, the user's fat mass.

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The indicators are evaluated every time the user interacts with the smart scale. From a short-term point of view, the indicators are expressed as single values. From a long-term point of view, time series can be evaluated as an ensemble of the short-term indicators.
No further data processing task is required in order to extract the indicators above listed. It is worth to notice the results reported in [1]. Author shows a comparison between the gold standard (SphygmoCor) and the Withings smart scale. As partial results, the author observes an overestimation of the body compositions. However, the study has limitations such as the observation of only five subjects. Observation during NESTORE pilot will take into account these findings with a focus on the reliability of the indicators directly evaluated from the smart scale.

4.1.1.3 Sleep quality indicators

People experience changes both in mental and physical aspect, especially as they age. One of these changes is related to the characteristics of their sleep habits: changes in pattern, sleep duration, and quality [2]. An accurate sleep monitoring is fundamental in order to detect early signs of sleep deprivation and insomnia, evaluating their sleeping habits, and consequentially implementing mechanisms and systems for preventing and overcoming these problems [3]. As a conclusion, better quality of life in elderly people may be achieved by increasing sleep quality [4].
In literature, sleep quality has been assessed using different techniques, including subjective and self-reported measures (e.g., the Pittsburgh Sleep Quality Index, the Consensus Sleep Diary, the Richards-Campbell Sleep Questionnaire, the Karolinska Sleep Diary) and objective measures (e.g., polysomnography and actigraphy). Recording several human sleep nights, considering an extended period, in a home setting with no restrictions, presumably better reflects habitual sleep than a highly controlled laboratory study conducted over a few consecutive nights. This suggest that more efforts should be spent to find reliable sleep monitoring system able to detect objective sleep quality characteristics strong correlated with findings of invasive clinical methods, self-report diaries, and actigraphy-based systems. It is worth noting that, especially in elderly and Ambient Assisted Living (AAL) scenarios, self-report diary approaches may be difficult to be used.

In this context, technological advances have allowed the development of non-invasive, long-life, battery powered, wearable devices equipped with tri-axial accelerometers (i.e., actigraphy) able to monitor and collect data generated by movements. Wearable devices for actigraphy, and in particular wrist-worn actigraphy devices, measuring sleep parameters have been validated through the comparison with polisomnography (PSG) [5]. [6] recommends the usage of actigraphy-based system concurrently with Consensus Sleep Diary (CSD) methodologies, in order to identify the period during which users are attempting to sleep. This combination of CSD and actigraphy is currently accepted as an alternative to the PSG methodology [7].

In NESTORE, all these suggestions are considered together. Basically, the idea is to perform the evaluation of: sleep stages identification (polysomnography represents the gold standard), perceived sleep quality (sleep diaries represents the gold standard), and variables able to characterize the sleep session (polysomnography represents the gold standard, but the actigraphy as previously described is considered a standard de-facto in home settings environments). At this purpose, the NESTORE system adopts the Ballistocardiography (BCG) technology to infer about the users’ sleep patterns, behaviour, and the sleep quality. BCG is a method for the measurement of the mechanical forces originating from the body. These systems are, in general, based on accelerometers. In a stationary state, primary mechanical forces acting on the body originate from the heart and circulation of blood. Beating of the heart is a cyclic event that is detectable. BCG enables accurate and non-invasive measurement of the cardiac and respiratory events in a stationary state, i.e. during sleep or rest. Unobtrusive BCG techniques for automatic sleep stage classication have provided good results in continuous home sleep monitoring [8]. The detected cardiac and respiratory events give information about the sleep quality. Heart Rate Variability (HRV) is an important parameter in BCG sleep analysis to distinguish between sleep stages [9]. It is worth noting that the differences between individuals must be taken into account. In fact, the typical HRV level can vary between individuals [10]. For example, aging and body weight have an effect on the BCG measurement [11].

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In the NESTORE system, the ballistocardiography is applied using the sensor SCA11H provided by Murata company. The BCG algorithm reports multiple parameters at 1 Hz frequency. The output parameters in BCG mode are timestamp, heart rate, respiratory rate, relative cardiac stroke volume, heart rate variability, signal strength, bed occupancy status and beat-to-beat intervals. Murata sensor requires a calibration with empty and occupied bed in order to detects the characteristic noise level of the bed and the environment. Occupied bed calibration was done for each test subject individually.

As shown in Table 1, the chosen short-term indicators are: perceived calm sleep, awakenings, time in bed, sleep stages, calm sleep, total sleep time, sleep onset, sleep onset latency, sleep offset, wake after sleep onset, and sleep quality index. It is worth noting that some indicators are useful from a long-term perspectives. In particular, perceived calm sleep, time in bed, sleep stages, total sleep time, and sleep quality index can guarantee a posteriori trend analysis, identifying significative differences in terms of sleep behaviour.

Table 1 Sleep quality indicators and evaluation methods

Variable Name	**SHORT-TERM**	**LONG-TERM**	**Evaluation**
Perceived Calm Sleep (PCS)	yes	yes	PCS indicates the auto-assessed sleep quality as it is perceived by the subject. The PCS value ranges from 1 to 5 and it is gathered through the mobile application provided by the NESTORE system.
Time in Bed (TB)	yes	yes	TB variable contain the start time and the end time of a users' sleep session. The algorithm for TB evaluation is based on a filtering process of the raw data and a mobile windows able to identify values different from zero. Assume a dataset time dependent $Raw(t)$ from $t = 1,2, \dots, T$. Then, the algorithm evaluate the first epoch (e.g., $t - t_n$) when $\sum_{i=1}^{w} Raw(i) > \partial$, considered with a fixed size w $(e.g., 30\ seconds, w = 30)$ and ∂ equal to a costant in order to avoid error due to noise. $TB_{start} = Raw(i)$. On the contrary, the same procedure is applied in order to evaluate the last epoch where the time series analysed epoch-by-epoch is close to zero TB_{end}.
Awakenings (AW)	yes	no	AW is a structure that contains: number of awakenings, the start time, end time and duration of each awakening event. This structure is evaluated in the morning analysing the raw data gathered from the BCG along the previous night. The algorithm for awakenings is based on a filtering process of the raw data coming from the sensors by the noise and applying a mobile windows in order to evaluate and to count epoch when the raw data are close to zero (ref TB).
Sleep stages: awake, REM, light and deep sleep	yes	yes	Sleep stages is a structure containing the start time and the end time of each sleep stage and the percentage of this stage referred to TB. The algorithm for sleep stages identification starts from the observation that the beat-to-beat times and the relative stroke value include a significant amount of noise. Consequently, the algorithm filter the raw data using a first order exponential filter of the form $y(t) = (1 - k) * y(t - 1) + k * x(t)$ n where $Y(t)$ and $y(t - 1)$ are the output values at time steps t and $t - 1$ respectively, $x(t)$ is the input value and k the filter coefficient. Furthermore, to get true sympatetic and parasympatic reactions it will be necessary to compensate the ratio between High/Low Frequency Beat2Beat time variation $HFHRV/LFHR$, extracted

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			from filtered heart rate variability HRV and heart rate HR values, with respiration depth calculated from Stroke Volume Variability SVV. By filtering with a 15 minute time constant and normalizing the initial value to 1, it is possible get the HRV. A similar procedure is applied in order to evaluate similar trends of HR and respiration rate variability RRV. Finally, applying a dynamic time warping analysis it is possible to detect the different sleep stages.
Total sleep time (TST)	yes	yes	TST is the time between sleep session start and sleep session end minus the time classified as awake (i.e. time occurred during nocturnal awakenings) $$TST = S_{off} - S_{on} - WASO$$
Sleep Efficiency (SE)	yes	no	SE is commonly defined as the ratio of total sleep time (TST) to time in bed (TB). $$SE = TST - TB$$
Sleep onset (Son)	yes	no	Sleep Onset is the time at which the subject falls asleep for the first time. Through the previously described sleep stages identification, it is possible to read the first epoch time when the subject falls asleep (ref. TB)
Sleep offset (Soff)	yes	no	Sleep Offset is the time at which the subject awakes and does not manage to fall asleep again. Through the previously described sleep stages identification, it is possible to read the last epoch time when the subject performs the last awakening event. (ref. TB)
Sleep onset latency (SOL)	yes	no	SOL represents the time that it takes to accomplish the transition from full wakefulness to sleep, normally to the light sleep. $$SOL = Son - TB_{start}$$
Wake after sleep onset (WASO)	yes	no	Wake after sleep onset is the total duration (minutes) of wake time after Son and it is calculated as the amount of time elapsed between sleep start and sleep end scored as wake. $$WASO = \sum_{i=1}^{y} AW(i)$$
Sleep quality index (SQI)	yes	yes	SQI express the objective users' sleep quality by analysing the variables previously described in terms of comparison with the "normal" statistics for subjects with same age and gender. SQI ranges from 1 to 5. In order to take into account, with different weights, all the variables, will be implemented a fuzzy logic algorithm. Fuzzy logic includes 0 and 1 as extreme cases of truth (in NESTORE the truth is equal to 5, as a condition of the best sleep quality) and includes various stage in between (from 2 to 4). A classic fuzzy logic control system requires three stages: fuzzy input (fuzzification), fuzzy logic processing, fuzzy output (defuzzification). During the fuzzification stage, in order to perform an input data association, it will be defined a membership function (as S shape). Secondly, the controller performs a rule evaluation and a fuzzy outcome calculation. Basically, the fuzzy logic uses a reasoning, or inferencing, process composed of *IF...THEN* rules, each providing a response or outcome. A rule is activated, or triggered, if an input condition satisfies the IF part of the rule statement

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		Finally, once a rule is triggered, meaning that the input data belongs to a membership function that satisfies the rule's *IF* statement, the rule will generate an output outcome. This fuzzy output is composed of one membership functions (with label), which have grades associated with it.

4.1.1.4 Non-structured Activity monitoring

A non-structured activity is represented by any kind of physical activity taken during the day, such as walking for transport, house-working, and performing any daily living activity.

Table 2 shows an example of the output from the wearable device for the daily living activity monitoring

Table 2 The output from the wearable device for daily activity monitoring

day	time			non-structured activity			steps [#]	distance [m]	stairs [#]	energy consumption [cal]
	start	stop	timezone	no/low activity	walking	running				
12/11/2018	08:00:00	09:00:00	2	00:40:00	00:20:00	00:00:00	420	400	20	30
12/11/2018	09:00:00	10:00:00	2	00:20:00	00:30:00	00:10:00	1325	1000	0	50
12/11/2018	10:00:00	11:00:00	2	00:20:00	00:30:00	00:10:00	1325	1000	0	50
12/11/2018	11:00:00	12:00:00	2	00:20:00	00:30:00	00:10:00	1325	1000	0	50

Here a detailed description of each field:

- *Non-structured activity*: the wearable shall monitor the user daily living activity recognizing 3 different levels of activity, namely *no or low activity*, *walking activity*, and *running activity*. Every hour, the wearable shall report the duration in minutes of these 3 different activity states.
- *Steps and distance*: user steps and distance monitored during daily activity are measured by the wearable through the use of an embedded accelerometer sensor and knowing the user medium step length. Every hour the wearable shall report the total steps and distance covered by the user.
- *Stairs*: During daily living, the wearable shall monitor the number of stairs climbed up by the user. This task will be performed using both accelerometer and barometer signals and the resulting stairs counting will be reported every hour.
- *Energy consumption*: Caloric energy burned by the user during the daily living. It is estimated by the wearable device using the heart rate information and knowing the type of activity performed by the user.

4.1.1.5 Sedentariness monitoring

Table 3 presents an example of the output from wearable device for the daily living sedentariness monitoring.

Table 3 Output from the wearable device for the sedentariness monitoring

day	sedentariness period	time		
		start	stop	timezone
12/11/2018	period #1	08:56:00	09:58:00	2
12/11/2018	period #2	10:40:15	11:50:32	2
12/11/2018	period #3	11:55:15	12:15:15	2
12/11/2018	period #4	14:40:15	14:50:15	2

Here a detailed description of each field:

- *Sedentariness behaviour*: in elderly, it is defined as any walking speed lower than 2.3 Km/h for men and lower than 2 Km/h for women [12] [13].

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- *Sedentariness period*: It is a period of time longer than 10 minutes in which the user is inactive or walking lower than the aforementioned velocities [14]. The wearable shall monitor these periods reporting the start and the stop time of each sedentary phase.
- *Exit criteria*: the system starts to record once the user achieves the aforementioned walking speeds.
- *Sedentary warning*: the user receives a warning form the system after 1 hour of sedentariness behaviour, then every 15 minutes.

4.1.2 Coaching exercise indicators

This section explains the variables used by the wearable to prescribe the structured physical activities. A structured physical activity consists in a planned, structured, repetitive, and purposeful physical activity aimed to improve or maintain one or more components of the user's physical fitness.

4.1.2.1 Exercise type

It is the exercise proposed by the coach to the Nestore user. It can be divided into two different groups:

- *Coaching activities*: they are the exercises chosen by the virtual coach in order to improve the NESTORE user aerobic fitness. Coaching activities that can be monitored by the wearable device are *walking* and *running*.
- *Coaching evaluation tests*: they are the exercises that permit to evaluate the actual state of the NESTORE user and estimate its changes during the pilot. Coaching evaluation tests can be summarized in two main areas: clinical aerobic fitness (i.e., *6 Minute Walking Test*) and clinical anaerobic fitness (i.e., *30 Seconds Chair Rise Test*). These evaluation tests are mainly monitored by the wearable device.

The *exercise type* is chosen by the coach and it is communicated to the wearable and to the other devices involved in the exercise measurement in order to properly start the monitoring.

4.1.2.2 Exercise intensity target (Target Heart Rate Range – THR)

This indicator refers to the Coaching Activities group. It represents the target heart rate range that the user shall maintain during the execution of a coaching activity. It is expressed in percentage with respect to the user's *Maximal Heart Rate*:

- *Light* intensity: 50-65% Maximal Heart Rate;
- *Moderate* intensity: 66-79% Maximal Heart Rate;
- *Vigorous* intensity: 80-95% Maximal Heart Rate.

The *exercise intensity* is chosen by the coach and it is communicated to the wearable and to other devices involved in the exercise measurement in order to properly start the monitoring.

4.1.2.3 Exercise target duration

This indicator refers to the *coaching activities* group. It suggests to the monitoring devices the target duration of a *walking* or *running* activity session. By design the user manually stops the acquisition. The target duration indicator, representing the goal suggested by the coach, is used to implement a power saving logic in the case of the user forgets to manually stop the acquisition.

4.1.2.4 Exercise duration

It represents the effective duration of the performed exercise. The wearable sends to the cloud the start and the end time of the exercise. The duration is computed in the cloud.

4.1.2.5 Exercise frequency

It is referred to the frequency of execution of a particular exercise performed by the user in a week. It represents the number of executions of a specific structured activity in a week. It is computed by a specific software module in the Nestore cloud (more details in document D6.4).

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4.1.2.6 Exercise heart rate

User heart rate during exercise is measured by the wearable device. All the heart rate indicators provided by the wearable are computed using a photoplethysmography (PPG) sensor. This sensor uses optical emitters to emanate light on the wrist skin and a photodetector to measure the scattered light. The measured scattered light is linked to wrist blood flow changes and permits to estimate the user heart rate.

In order to limit the data amount sent from the wearable device to the cloud, the wearable shall not send the global heart rate timeseries collected during the exercise session, but a report summary of the heart rate activity:

- *Time in the different heart rate zones* (exercise intensity ranges): this indicator refers to the *coaching activities* group. It is the time passed in the different *exercise intensity* range during the activity execution (e.g., light intensity: 5 minutes; moderate intensity: 6 minutes; vigorous intensity: 1 minute; severe intensity: 1 minute).
- *Peak heart rate*: it is the maximal heart rate collected during the exercise execution.
- *Post exercise Heart Rate Recovery (HRRec)*: it represents the difference between the user heart rate measured immediately after the exercise stopping and the user heart rate measured 2 minutes later.

4.1.2.7 CardioResp score

This indicator refers to the *coaching activities* group. It is a score assigned to the user for the executed coaching activity. It shall be computed on the cloud considering the selected *exercise intensity target* and the *time in the different heart rate zones* indicators provided by the wearable. The score is equal to:

- For light intensity exercise: 1 point for every 10 minutes of activity, with a minimum exercise duration of 10 minutes;
- For moderate intensity exercise: 2 points for every 10 minutes of activity, with a minimum exercise duration of 5 minutes;
- For vigorous intensity exercise: 4 points for every 10 minutes of activity, with a minimum exercise duration of 2.5 minutes.

The final score is computed considering the time passed in each heart rate zone and its associated score rate. The score points are assigned to the user if the sum of the exercise duration at intensity greater or equal to the intensity target exceeds the minimum exercise duration of the target intensity.

4.1.2.8 Training adherence

User's adherence to the coaching plan will be assessed using the adherence score, which is defined as the ratio between the score obtained in a single session and the score planned in the schedule for that session, multiplied by 100.
For example:

Exercise type: running;
Exercise intensity target: moderate;
Exercise duration: 20 minutes;

Time in the different heart rate zones recorded by the wearable during activity:

Light intensity: 2 minutes;
Moderate intensity: 13 minutes;
Vigorous intensity: 1 minute;

CardioResp score = 0.1*2+0.2*13+0.4*1 = 3.2
Adherence score = [(0.1*2+0.2*13+0.4*1) / 0.2 * 20] * 100 = (3.2 / 4) * 100 = 80%

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4.1.2.9 Steps and Distance

User steps during exercises are measured by the wearable through the use of an embedded accelerometer sensor. Noted the user medium step length, the distance covered by the user during the exercise can be estimated by wearable using the steps information.

In order to limit the data amount sent from the wearable device to the cloud, the wearable shall not send the steps and distance timeseries, but just the total steps and total distance covered by the user in a specific exercise. Especially for the 6MWT exercise, the distance is computed in a more accurate way using also the GPS of the user smartphone. It should permit to enhance the measured accuracy and to have a more detailed information about the walking path and the test execution modality.

4.1.2.10 Pseudo-Six Minutes Walking Test (Pseudo-6MWT)

The Six Minutes Walking test (6MWT) is a standardized test used to define the residual functional capacity of a patient and it is usually recommended as diagnostic tool. In order to have a value and be comparable, the 6MWT must be performed in a controlled context: the test should be done always in the same way, in order to obtain comparable results, carried out indoors with a well-defined path (without slope, on flat corridors of about 30 meters) and with a turn about every 30 meters. This kind of test needs to be performed in a controlled environment, under the supervision of clinical staff. For this reason, Nestore implements a pseudo-6MWT. The pseudo-6MWT is a 6MWT auto-administered outdoor but with the supervision of the smartphone. The smartphone suggests to the user the timing and the instruction on how complete the pseudo-6MWT. The user walks for six minutes while the wearable record steps and distance data. These data, measured from the wearable, are then compared with other more accurate data recorded by the smartphone (GPS, altimeter, etc.). The pseudo 6MWT compare all the data and validate the test only if the path and, eventually, the slope followed during the test are in a predefined range. Being all the test performed validating them with the same range of values, these can be compared intrasubjectively.

4.1.2.11 Elevation gain or Total ascent

This indicator refers to the *coaching activities* group. It is the sum of every gain in elevation reached by the user throughout an entire walking or running activity. It is computed using the barometer sensor embedded in the wearable device. The barometer, indeed, permits to measure the atmospheric pressure and its changes are related to altitude variations.

4.1.2.12 Number of squat repetitions

This indicator refers to the 30SCRT exercise. It indicates the number of squat performed by the user during the test execution. It is estimated by the wearable using both accelerometer and barometer sensors. This indicator could be refined on the cloud applying more complex algorithms on the same data to understand if the test has been well executed by the user.

4.1.2.13 Energy consumption

Caloric energy burned by the user during a specific exercise. It is estimated by the wearable device using the heart rate information and knowing the type of activity performed by the user.

4.1.2.14 Rate of perceived exertion

The Rate of Perceived Exertion (RPE) is a quantitative measure of perceived intensity during physical exercise. Perceived exertion is how hard you feel like your body is working. It is based on the physical sensations a person experiences during physical activity, including increased heart rate, increased respiration or breathing rate, increased sweating, and muscle fatigue. Although this is a subjective measure, a person's exertion rating may provide a fairly good estimate of the actual heart rate during physical activity. Perceived exertion will be assessed using Borg Scale 6-20. User will report his RPE in the chatbot app immediately following exercise cessation.

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The computation is performed on the cloud using the questions/answers provided by the chatbot (soft data).

4.1.2.15 Fatigue accumulation

Fatigue is defined as a sense of persistent general tiredness. It is becoming increasingly recognized as a specific geriatric entity since both prevalence and incidence appear to increase with advancing age, and for the majority, fatigue per se exists independently of any specific diagnostic conditions. Task-specific measures of tiredness have been examined in clarification of the theoretical assumption that fatigue may be instrumental in the disablement process. In particular, self-reported tiredness while performing daily activities has been examined, and among non-disabled elderly people, it has been found to be a determinant of subsequent utilization of health and social services, walking limitations, onset of disability, and a reduction in both 10- and 15- year survival. Fatigue accumulation will be asked to the user 12 hours following exercise cessation in the chatbot using Total Quality of Recovery scale.

The computation is performed on the cloud using the questions/answers provided by the chatbot (soft data).

4.2 Nutrition

The recognition of users' habits in the nutrition field is one of the key elements in NESTORE and one of the main parts of the personalization process. In fact, we can talk about Personalized Nutrition in the sense that we provide ad-hoc recommendations and activities based on both users' intake of nutrients and users' behavioural choices.

The main sources of information in the case of nutrition are a) users contributing with information about behavioural aspects and preferences through the different interfaces of the NESTORE Coach (WP5) and b) the LogMeal API; an intelligent nutrition monitoring system developed in the framework of WP3 which aims to recognize food from images taken by a smartphone.

In contrast to other coaching tools available in the market (like *Lose it!*[1] or *MyFitnessPal*[2]), which demand users to fill in long questionnaires about nutrition, NESTORE relies on an application based on automatic food recognition. This software seeks to recognize different foods/beverages/ingredients and interprets its nutritional composition by translating the picture of a food into a list and quantity of ingredients. Afterwards, the DSS extract the nutrients by using a food composition database. The resulting dataset is constructed on the basis of official European food composition databases. Moreover, the recipe ingredients database is elaborated through the consultation of various sources of information (mainly recipe books) in order to avoid a skewed approach in its design.

As a result, the exploitation of the dataset containing the records of all foods and beverages consumed during a period of time provides the average nutritional and energy intake of the subject. In parallel, Dietary Reference Values (DRV) for each nutrient, meaning the recommended intakes that are set to meet individual needs, have been established for Nestore users. DRVs are used within the system to identify possible deviations in user's nutrient intakes. Energy intake needs are set taking into account the individual energy expenditure, measured by sensors or equations, and phenotype (e.g. normoweight, obese…), obtained from user's input and/or devices.

[1] https://www.loseit.com
[2] https://www.myfitnesspal.com/

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Finally, the assessment of the nutritional status of Nestore users is intended to be translated in clear, comprehensible and simple dietary recommendations made on common foods or food groups intake (not on nutrients) and adapted according to their dietary preferences. Such recommendations are performed by two types of messages: in a first place, the user receives an immediate feedback (e.g. regarding his/her nutritional status or the meal inserted) and in a second place, the system transmits messages with recommendations focused on the long-term dietary habits modification. In order to assess and monitor the adequacy to this recommendations, a short *follow-up* questionnaire will be administered at night to get users' feeling about the proposed plans and adequate further recommendations to users' preferences.

4.2.1 Nutritional indicators

Due to the fact that the recognition of nutrients and energy intake leads the personalization process in this domain (see document D2.1), we define *nutritional indicator* as nutrient-status, energy intake and other dietary parameters with potential health relevance for the target users.

The process of extracting nutritional indicators to personalize users' recommendations goes through the following stages:

1. NESTORE Coach receives a new photo of a meal.
2. The photo is sent to the DSS together with some metadata (user identification and type of meal – breakfast, lunch, snack or dinner -).
3. The DSS interacts with the LogMeal API (see document D3.3), which analyses the photo and sends back meal information about the recognized food.
4. The DSS process the information gathered from the LogMeal API and sends to the user via the Coach a list of possible dishes.
5. The user confirms the dish either by:
   a. selecting one of the dishes proposed by the system

   or

   b. writing the name of the dish with the help of an autocomplete input element

   or

   c. choosing food groups contained in the dish
6. The DSS receives the name of the confirmed dish and gathers the receipt from the LogMeal API.
7. The DSS calculates the nutritional indicators.
8. The DSS saves data in a MongoDB instance for further analysis.

Besides, some algorithms run off-line to fuse and analysis all the gathered data. When the system finds any interesting situation it reacts taking the necessary decision.

In this deliverable, we focus on the extraction of indicators, while the recommendation process and algorithms will be described in further deliverables of WP4 (documents D4.2, D4.3.2, and D4.4). As listed in document D2.1, various nutritional indicators are advised to be extracted by NESTORE system. In Table 4 we list them, explaining how they are evaluated and if they apply to the short-term and/or the long-term.

Table 4 Nutritional indicators and evaluation methods

Variable Name	**Short-term**	**Long-term**	**Evaluation**
Food Intake	yes	yes	Photos of the dishes are provided by the user and sent to the system through the so-called NESTORE Nutrition API. A dataset containing the name of the dish, the type of meal (breakfast, lunch, dinner or snack) and the timestamp is constructed.

Nutrient Intake	yes	yes	After the user confirms the name of the dish, the recipe is extracted from the NESTORE database of recipes and afterwards, the following nutrients are calculated through a food composition database: water, protein, carbohydrates, simple sugars, fat, cholesterol, fiber, Vitamin D, Vitamin B12, Vitamin C, Vitamin A, Vitamin B-6, Vitamin E, Folic Acid, Sodium, Iron, Zinc, Selenium, Magnesium and Alcohol. The grams of each nutrient are accumulated to come up with a daily nutrient intake summary.
Number of meals	yes	yes	The number of meals per day is calculated checking the different types of meals included by the user each day. In the case that the user selects a pathway related to nutrition, the number of entered meals is one of the main elements to control the user engagement.
Intake of supplements	yes	no	The intake of supplements is asked to the user through the chatbot during the first weeks. Afterwards, it is used in the platform to evaluate the recommendations of nutrients.
Refused Foods	yes	no	The term refused foods is associated with allergies, intolerances, diets and foods that are not consumed by the user due to personal preferences. The list of refused foods is gathered from the user directly by means of a conversation thread executed through the chatbot (WP5).
Basal Metabolic Rate (BMR)	yes	no	The BMR is the energy consumed by the user in order to maintain basic metabolic functions. It is calculated using the *Harris and Benedict* equation: • MEN: 66.473 + (13.752 x body weight (kg)) + (5,003 x height (cm)) – (6.755 x age (years)) • WOMEN: 665.1 + (9.563 x body weight (kg)) + (1.85 x height (cm)) – (4.676 x age (years)) Therefore, the system needs to collect from the user the gender, date of birth, weight and height to perform the calculations.
Activity Energy Expenditure (AEE)	yes	yes	The activity energy expenditure is the energy expent in physical activities not related to the maintenance of vital body functions. Therefore, the way to obtain this energy expenditure is equivalent to the one explained in physical activity section.
Energy Intake (EI)	yes	yes	The energy intake is the energy contained in foods consumed by the user. It is derived from the food intake indicator. The calculation of this indicator is detailed in the following chapter of this document.
Total Energy Expenditure (TEE)	yes	yes	The total energy expenditure is calculated as the sum of the BMR and the AEE and it is all the energy that a user expends during 24 hours. It is used to recommend the amount of energy needed to consume.

A detailed example of how we extract these indicators, with a focus on *Food Intake* and *Nutrient Intake*, together with the communication paradigm and implementation details is presented in Appendix 2. Nutritional indicators - Example of indicators extraction, communication sequences, and technical details.

4.3 Cognitive and Mental Status and Social Behaviour

In the **cognitive domain**, two characteristics of individuals are considered: (1) Inter-individual differences in the cognitive performance status of individuals that are assessed once before (at baseline) and once after (at posttest) the coaching intervention. Some of the cognitive status variables will be assessed within the system and are fed into the DSS to contribute to the system's recommendations for a given coaching domain (i.e., the n-back task and the numerical memory updating task). Others will be assessed in the pilots during the baseline visit at participants' homes using paper-pencil tests to use the information for the evaluation of the effectiveness of the intervention, but not as part of the DSS. Part of this inter-individual status information beyond objective test scores is the assessment of self-reported memory failures (i.e., the CFQ questionnaire). These status variables can be considered long-term indicators as they are used to eventually determine change (or stability) in functioning in this domain. They do, however, contribute to the DSS for the initial recommendation about coaching domains. (2) Two types of cognitive performance fluctuations are assessed in daily life. Both of these reflect the same cognitive domain, working memory. One type of task will be assessed repeatedly (as part of the coaching messages and assessment time-flow: 3 times per week rather than daily to ease participant and user burden) in the entire user group to track their cognitive functioning in everyday life (i.e., the digit span backwards task). The other type of indicator is related to the cognitive coaching (i.e., structured training) intervention and thus is only assessed for those individuals who select the cognitive domain and therein a given cognitive pathway (i.e., the numerical memory updating task). There are three cognitive pathways in NESTORE: (a) A structured working memory training task that is performed as part of the App on users' smartphones, for which accuracy is the outcome to be tracked (that is, the numerical memory updating training), (b) part of the serious game suite developed as part of the NESTORE system for which reaction time and accuracy need to be tracked as outcomes and targets broader thinking skills, and (c) unstructured novel and challenging activities people chose to engage in that need to be tracked in terms of whether and how frequently the activity has been performed or not.

4.3.1 Cognitive functioning at baseline

Participants perform several tasks at baseline during the pilots which measure different cognitive domains (e.g., working memory, perceptual speed, general cognitive ability, self-reported cognitive failures). Two of these will be assessed as part of the NESTORE App at baseline and post assessment and be fed into the DSS to determine coaching domain recommendation, the N-Back task (Working Memory 1; WM1-NB) and the numerical updating task (working memory 2; WM2-NU). Further, the data of these tasks will be used for sub-study 1 of the pilot study to determine the effectiveness of the coaching interventions in terms of cognitive benefits. Table 5 shows an overview of the chosen indicators and the evaluation methods.

Table 5 Cognitive functioning at baseline indicators and evaluation methods

Variable Name	**SHORT-TERM**	**LONG-TERM**	**Evaluation**
WM1-NB	no	yes	In the WM1-NB individuals are asked to memorize a string of numbers and decide for each numeric stimulus presented whether it is identical to the number presented one or two positions backwards. Reaction time and proportion correct (hits + correct rejections) are the main outcomes to be recorded and proportion correct will be used as criteria for coaching domain recommendation. The WM1-NB task will be provided by the NESTORE system.
WM2-NU	Yes (part of the training; see below)	Yes	In the WM2-NU task individuals need to perform numerical updating operations (+ and -) across 2-4 cells and memorize the final result in each cell after a series of such operations. Proportion correct is the main outcome. This task will be

			provided by the NESTORE mobile system as part of the App on smartphones or tablets and is the main part of the structured cognitive training.
Memory Failures (MF)	Yes (see below)	Yes (long version Questionnaire)	In the MF individuals will provide ratings on the items of the Cognitive Failures Questionnaire (CFQ) that assess the experience of memory failures across various domains (memory for names, locations, things, actions etc.). The MF items will be provided by the NESTORE system (chatbot or App) and the users will indicate the level of failure on a 1 to 5 scale. The mean across item responses needs to be computed and will be used for the DSS.

4.3.2 Cognitive performance in daily life

Cognitive status for all users will be tracked through the daily evaluation of a working memory task that will be implemented on the smartphone/tablet (i.e., digit span task). This will provide us with information on the objective cognitive performance within the users' everyday context. It is well known that cognitive performance fluctuates on different time scales, from trial to trial, from test block to test block, and from day to day [15]. Since assessing cognitive performance multiple times a day in order to obtain information on the test block to test block variability should be too much of a burden for NESTORE users and therefore not feasible, we will assess cognitive performance 3 times per week, in order to obtain information on the daily variability and fluctuations in cognitive performance.

In addition to objective cognitive performance, we will also assess subjective cognitive performance (i.e., everyday performance such as Memory Failures; MF) on the daily level. Often, subjective and objective cognitive performance are not highly correlated and therefore the subjective assessment may provide additional information on the overall cognitive status of the NESTORE user. To do so, we will use single items form, the Cognitive Failure Questionnaire (CFQ) [16], an instrument that assesses memory, perceptual and motor failures in peoples everyday life.

4.3.3 Cognitive training performance

The coaching intervention in the cognitive domain consists of three pathways: The first cognitive coaching pathway is a traditional **cognitive training task**, **numerical memory updating** (a measure of working memory), that requires users to perform several numerical operations in a row and remember the results for sets of 2 to 4 numbers. This task will be adaptive, i.e., difficulty level (set size) will continuously increase from 2 to 4 depending on the performance accuracy of each person. For this task, we need to track proportion correct across blocks per day. The DSS needs track whether participants have engaged in the game as scheduled if this is the pathway they selected, so that the DSS can prompt users with the appropriate behaviour change messages of encouragement, reminders and prompts.

The second cognitive coaching pathway is for participants to "play" a **serious game** that is designed to challenge and thus train multiple cognitive domains in parallel. This game is being developed by TU Delft on the basis of a previously developed and evaluated serious training game at UZH [17]. Specifications have been provided to TUD in terms of the to-be-tracked and recorded outcome variables and the adaptive adjustment of the difficulty level across training sessions depending on the current performance of the user, that need to be integrated into the DSS to provide feedback to participants. It is mainly important for participants to obtain that performance feedback somewhere. The DSS needs track whether participants have engaged in the game as scheduled if this is the pathway they selected, so that the DSS can prompt users with the appropriate behaviour change messages of encouragement, reminders and prompts.

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The third cognitive coaching pathway is for participants to begin a **new and complex activity**. For this part, it needs to be tracked through follow-up questions whether participants have engaged in the activity that they will have to schedule in their NESTORE agenda and to briefly reflect on how they enjoyed the activity or what they have learned from it that particular visit and to prompt users with the appropriate behaviour change messages of encouragement, reminders and prompts.

Table 6 shows an overview of the chosen indicators with the corresponding evaluation methods.

Table 6 Cognitive training performance indicators and evaluation methods

Variable Name	**SHORT-TERM**	**LONG-TERM**	**Evaluation**
WM3-DSB	yes	no	In the WM3-DSB individuals are asked to recall a series of digits in the reverse order. The participant will be presented with multiple trials of varying length (e.g., 2 to 8 digits). To evaluate performance on the WM3-DSB, the mean accuracy (number of correct digits on the correct location) across all trials will have to be computed by the system. The DSB will be provided by the NESTORE mobile system.
MF	yes	Yes (see CFQ Questionnaire)	In the MF questionnaire (i.e., subjective cognitive assessment), individuals will answer 10 items (different from CFQ, specifically designed to measure memory failures in daily life) regarding possible memory failures on that given day. The MF items will be provided by the NESTORE system and the users will indicate the occurrence or not of any failure on a 0 (no) vs. 1 (yes) scale. Responses will be summed across items to obtain the daily MF score.
WM1-NU	Yes (training group only)	Yes (see above)	In the WM1-NU task individuals need to perform numerical updating operations (+ and -) across four cells and memorize the final result in each cell after a series of such operations. Proportion correct is the main outcome. This task will be provided by the NESTORE mobile system as part of the App on smartphones or tablets.
COG-G	yes	no	Serious game to train multiple cognitive domains simultaneously. Tracking needs to occur in terms of whether individuals engaged in the training session, the level of difficulty, and the accuracy.
Cognitive activities (as part of coaching)	yes	no	Tracking needs to occur in terms of whether the activity has been engaged in at each scheduled occasion and how users enjoyed it.

4.3.4 Mental states in daily life: Motivation/Health behaviour change (HAPA) variables and emotion

In order to examine the motivational state of NESTORE users along the user journey, we will assess several variables that are part of the theoretical model underlying the intervention design, the Health Action Process Approach (HAPA) model. These variables cover the following constructs: motivational self-efficacy, risk awareness, positive outcome expectancy (all assessed at the beginning and towards end of first two-week assessment period, intention, recovery self-efficacy, action planning, coping planning, and action control (all assessed once the coaching pathway has been selected, the intention to change one's behaviour formed, and the intervention begins). For the DSS, the relevant variables are intention formation and the planning variables, as well as action control and recovery self-efficacy. These are all assessed as single items and no computation is required by the system.

In the mental domain, we mainly assess emotional experiences that are also subject to daily fluctuations and an important indicator of well-being on a short-term basis. To assess daily fluctuations in self-reported emotions, we will use daily and short versions of the questionnaires MDBF [18] to assess dimensional emotional experiences, and of the DEQ [19] to assess discrete emotional experiences in daily life. These questions can be prompted via smartphone or the chatbot. It would be mandatory that they are administered on a daily basis, however. Further, emotional experience (i.e., dimensional and discrete emotions and overall sentiment valence) will also be detected from the text analysis tool implemented in the chatbot of NESTORE to gain a complementary insight into the emotional status (beyond self-report) of the NESTORE users.

In addition to emotional experiences, we will also assess acute stressors in daily life. This will be done either using the Daily Inventory of Stressful Experiences (DISE) Questionnaire (comprising 6 items with yes/no and severity of stressor experience) [20] or a single item asking for the presence and severity of any daily stressor on a given day. Together, the wellbeing and daily stress items provide general information on the day-to-day mental status of NESTORE users so that the system can detect if things are generally going well or rather not.

Table 7 shows an overview of the chosen indicators with the corresponding evaluation methods.

Table 7 Mental states in daily life indicators and evaluation methods

Variable Name	**SHORT-TERM**	**LONG-TERM**	**Evaluation**
HAPA	yes	no	(1) Single items each of: motivational self-efficacy, risk awareness, positive outcome expectancy (all assessed at the beginning and towards end of first two-week assessment period, (2) Single items each of: intention, recovery self-efficacy, action planning, coping planning, and action control (all assessed once the coaching pathway has been selected, the intention to change one's behaviour formed, and the intervention begins). As these are single items, no computation is necessary. The DSS needs to react by sending appropriate Behaviour Change Technique (BCT) messages depending on the values on several of these HAPA variables.
MDBF	yes	yes	In the MDBF the individuals will answer single items of the scale and do so on a scale ranging from 1-5. Depending on how many items will be used, a mean score across the items needs to be computed. Text analysis via chatbot: Chatbot will provide texts of users in terms of reflections of their day from which it will be then extracted the dimensional emotional state information ("*EMOTIVE Wellbeing Engine").*
DEQ	yes	yes	In the DEQ the individuals will answer single items of the scale and do so on a scale ranging from 1-7. Depending on how many variables will be used, a mean score across the items needs to be computed.
Acute Stress	yes	no	Two items: Stressor occurrence and stressor severity. No computation required.

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			In addition: automatized detection form text tools ("EMOTIVE Well-Being Engine, part of Work Package 5 activities). This automated analysis will produce a set of scores as output of the analysis of the emotional states and sentiment and stress that are relevant at short-term.
Sentiment Valence	yes	no	Automatised detection form text tools ("EMOTIVE Well-Being Engine, part of Work Package 5 activities). This automated analysis will produce a set of scores as output of the analysis of the emotional states and sentiment and stress that are relevant at short-term.

4.3.5 Social behaviour and experiences in daily life

Social behaviour will also be tracked via self-reported questionnaires and objective information assessed via the sensing tools for the entire user group and with respect to the coaching activities for the intervention group that selects the social domain. Regarding the self-reported information, we will ask individuals for two different kinds of information: 1) type of social interaction and 2) loneliness on a given day. The type of social interaction will be assessed by asking them "Did you have contact with anyone today"? If yes, they may indicate the number of social interactions and indicate the respective role of the individual they had contact with to indicate the social role (i.e., the partner, children, friends). To assess loneliness, we will use 2 single items from the De Jong Gierveld scale to cover daily social and emotional loneliness [21].

Human interactions are governed by the explicit willingness of establishing meaningful social relationships. Recognizing social interactions between humans is a complex and extremely diversified field. Face-to-face interactions detection often depends on the phenomena under observation: in certain cases only short events with a very small distance between the individuals are relevant, in others, only prolonged proximity that would give individuals a chance to have meaningful conversations are pertinent. A tie between two individuals is defined as a combination of the amount of time, the emotional intensity and the reciprocal intimacy that characterizes the tie itself [22]. More clearly, each tie is a link between humans, and its strength depends on several factors [23], such as the frequency of their interactions, the intimacy level, and the affinity of the subjects involved. Several ways to analyse human behaviour exist, for example through a direct or indirect observation of their actions. One of main issues of a direct observation is the observer itself since may influence the natural behaviour of individuals. Moreover, self-reported questionnaires are useful to understand social activities but request an active participation of the individuals and may not be the optimal solution, in case of fragile and older people. Surveys offer a coarse view of reality, as people might forget to report [24]. The passive and automatic detection of social interactions is an emerging research field, which helps revealing complex dynamics of the society with high resolution. Usually, two main constraints have to be faced when trying to capture such interactions automatically: the need to collect accurate and reliable data and the need to have large deployments to get a clearer picture of human behaviour.
In literature, human interactions has been assessed using different techniques, including subjective and self-reported questionnaires, and technologies, such wearable devices equipped with dedicated hardware [25], [26]. Many solutions have been proposed using several different technologies, for instance Radio-Frequency IDentification (RFID) [27], Zigbee radio [28], infrared sensors [29] and environmental sensors [30]. In NESTORE, our attention is directed towards Bluetooth Low Energy (BLE) technology. The potential of BLE to detect people proximity has been tested in some works by evaluating both accuracy and power consumption, using ad-hoc wearable devices [31], smartphones [32] and tags [33]. Solutions are based on the analysis of the Received Signal Strength Indicator (RSSI) emitted by BLE beacon transmitters and received by the user personal device. The solution adopted in NESTORE relies on a multifunctional wearable device, as a BLE beacon receiver and emitter, and on BLE Tags as BLE beacon emitters. Both devices have been developed and produced by FLEX and are described in D3.1 and D3.2 documents. Users will be equipped with the wearable device which will collect BLE beacons during the daily hours. Each pilot site will be endow with ten BLE tags, subdivided in two categories: five tags will be installed inside houses in different rooms, such as living room, kitchen or bedroom, to infer the user movements and the location of the occurred meetings; five tags will be assigned to relatives and friends. A novel algorithm has been designed to detect social interactions by analysing BLE beacons. The

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goal of algorithm is to accurately estimate the start and the end time of all the interactions between all the possible dyads in a group of people (i.e. each pair of devices in proximity). The algorithm processes the raw data collected from all the devices, in terms of RSSI values, and it reports a time series of found interactions. As shown in Table 8, the chosen short-term and long-term indicators are: social interactions detection, total number of interactions, interactions duration and interaction locations. The last three indicators are estimated starting from meetings detection and are useful for a long-term and a-posteriori trend analysis, identifying significative differences in terms of social behaviour along time.

Table 8 shows an overview of the chosen indicators with the corresponding evaluation methods.

Table 8 Social behaviour and experiences in daily life indicators and evaluation methods

Variable Name	**SHORT-TERM**	**LONG-TERM**	**Evaluation**
SI	yes	no	The individuals will be asked by the end of the day: 1) "Did you have contact / a social interaction with anyone today?" 2) If no (END of questionnaire), if yes → 3) How many instances of social interactions did you have → enter number 4) Please indicate for each instance, with whom you had contact with (users may select form a list of social roles) Results from 2), 3) and 4) should be stored but don't need to be further analysed.
Loneliness	yes	yes	Two single items that assess the feeling of social and emotional loneliness will be used that are adapted from the long-version of the loneliness questionnaire from [21]. The average of the ratings across these items needs to be computed.
Social interactions detection (SID)	yes	no	Once a day, typically in the night, the meetings detection algorithm will be run to estimate the user social activity of the previous day. The calculation will be done on the cloud and will provide a list of all the occurred interactions. The analysis is based on RSSI values elaboration during a sliding time-window. Assuming a dataset format as follows: <*epochtime, datetime, id receiver, id sender, rssi*>, the algorithm will evaluate the following *opening condition* during the sliding time-window of duration Δ_{up}: • to receive at least p% of the expected beacons; • the RSSI of the received beacons is greater or equal the threshold value τ_{rssi}. Once the meeting is detected, it holds until the *closing condition* is detected: the time interval between the last received beacon with RSSI $\geq \tau_{rssi}$, is greater than or equal to Δ_{down}. At the end of the analysis, the algorithm will report a time series of the found interactions between the user (U_i) with other individuals ($I_1, I_2, \ldots, I_m$). The output of the algorithm will be a vector composed by the start and the end time of the interactions occurred with each individual: U_i=[(I_1,[t_{start},t_{end}]), (I_2,[t_{start},t_{end}]), …, (I_m,[t_{start},t_{end}])]

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Total number of interactions (TNI)	yes	yes	Given the interactions detected (SID), the total number of interactions (TNI) will provide an estimate number of occurred meetings by the user during a observation time lapse. The frequency of the analysis can be configured for a short-term (hourly,daily) or long-term (weekly,monthly). $$TNI_i = \sum_{d=i}^{k} size(U_i)$$ where d is the selected time scale.
Interactions duration (IDD)	yes	yes	Given the interactions detected (SID), the interactions duration (IDD) will provide an estimate time duration of occurred meetings by the user during a observation time lapse. The frequency of the analysis can be configured for a short-term (hourly,daily) or long-term (weekly,monthly). $$IDD_i = \sum_{d=i}^{k} duration(U_i)$$ where d is the selected time scale and duration is time interval (t_{end}-t_{start}) of all interactions.
Interaction locations (IL)	yes	yes	Given the interactions detected (SID) and the list of BLE tags distributed in the indoor environment, the algorithm will correlate the interactions among individuals with signals received from specific locations. The frequency of the analysis can be configured for a short-term (hourly,daily) or long-term (weekly,monthly). The output will be a vector composed by the id number associated with the specific location (L1, L2, …, Ln), the start and the end time of the interactions occurred with each individual (I_1, I_2, …, I_m): IL_i=[L_1: (I_1,[t_{start},t_{end}]), (I_2,[t_{start},t_{end}]), …, (I_m,[t_{start},t_{end}]) L_2: (I_1,[t_{start},t_{end}]), (I_2,[t_{start},t_{end}]), …, (I_m,[t_{start},t_{end}]) … L_n: (I_1,[t_{start},t_{end}]), (I_2,[t_{start},t_{end}]), …, (I_m,[t_{start},t_{end}])]
Social activities (as part of coaching)	yes	no	Track whether and which activities a person engaged in and response to enjoyment question.

A detailed view of the algorithms used for the social interaction detection and the preliminary results obtained on experimental data is presented in Appendix 3. Preliminary Assessment of Social Indicators.

4.3.5.1 Social activities as part of social coaching

The social coaching in NESTORE involves two pathways: The first pathway is to improve social integration by **joining (new) social group activities** that are in the areas of interest of the participant. The system will need to record whether the (and which) activity has been engaged in and record also responses to follow-up questions on enjoyment. We also need this information to prompt users with the appropriate behaviour change messages of encouragement, reminders and prompts.

The second pathway involves attendance in more **structured social skill training** classes. Again the system needs to record engagement in these courses (which course, attended or not, enjoyed or not) as scheduled and to prompt users with the appropriate behaviour change messages of encouragement, reminders and prompts.

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4.3.5.2 Considerations on the use of voice activity indicators

As one indicator of social interactions, **voice activity** could be recorded using the Electronically Activated Recorder (EAR) [34]. This is an app available for smartphones which records ambient sounds from the environment in a pre-specified time schedule (typical schedules include 30 secs snippets every 12 minutes or 90 secs snippets every 18 minutes). The resulting sound files are often transcribed and coded using coding schemes that depend on the specific research question (e.g., whether couples talk about a given disease; whether autobiographical references are made in terms of past, present and future time references, etc.) [35] [36].

New developments in the field provide the less time consuming more automatized detection of human voice across sound-files which can be aggregated to form an indicator of the proportion of time human voice and thus presumably social interactions (either F2F or via phone) have taken place [36]. Even though this approach provides unique insights into contextualized social interactions (if one were to code context information and use in the analyses), there are some important ethical considerations using this approach. Unconsenting third-party individuals are also recorded. It is common practice in this line of research to have an extensive information of participants in what the research is about and why these recordings are necessary, that they cover in total only about 1-2% of the waking ours of a given day and are thus rather unobtrusive, but still informative from a psychological point of view. There is a mute function that allows participants to mute the microphone for x minutes in situations where they wish to not be recorded.

As for the third-party, the transcription and coding only involves the target person, and in the NESTORE context we would only analyse the human voice presence without any further in-depth content analysis. The requirements on ensuring privacy differ from country to country and ethics committee to ethics committee. UZH has a successful track record of collaboration with Prof. Matthias Mehl (University of Arizona) in using the EAR in various studies, after following a strict ethics protocol that could be shared within NESTORE.

It seems less feasible to acquire the ethics approval in all pilot sites in time for the planned pilot starting date, however. We therefore currently refrain from including this option into the NESTORE system and rather track social interactions using self-reports and other sensing data as complementary to each other. In case of a later inclusion, we will describe it as environmental sensor in D3.2.

4.4 Other indicators from environmental sensors

In this Section, we describe all the environmental indicators that are transversal with respect to the five NESTORE domains identified in the document D2.1. These indicators refer to a wider meaning of user well-being and they are useful to detect a more general context of the user, in particular related to the status of his environment. The indicators extracted in this field directly derive from Task 3.2 activities, in terms of environmental sensors. The source of information for these indicators is hard data, in particular BLE beacons embedding humidity and temperature sensors and their peculiar capability to detect proximity based on Received Signal Strength.

4.4.1 Thermal environment condition indicators

Indoor Air Quality (IAQ) is a major concern to businesses, schools, building managers, tenants, and workers because it can impact the health, comfort, well-being, and productivity of the building occupants. The OSHA guidance document [37] on IAQ provides practical recommendations that help preventing or minimizing IAQ problems in buildings, and helps in resolving such problems quickly if they do arise. In the document, temperature and humidity are recognized as important because thermal comfort underlies many complaints about “poor air quality.”

Among the important practices suggested, the more related to residential building include:

- Check whether the temperature and humidity are maintained in a recommended comfort range (temperature: 20 to 25 Celsius degrees and relative humidity: 30% to 60%).

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This condition is directly suggested by the ANSI/ASHRAE Standard 55-2010 [38]. The purpose of this standard is to specify the combinations of indoor thermal environmental factors and personal factors that will produce thermal environmental conditions acceptable to a majority of the occupants within the space. The environmental factors addressed in this standard are temperature, thermal radiation, humidity, and air speed; the personal factors are those of activity and clothing. Also in this document, temperature and humidity are indicated as the more objective and easy to manage factors to detect and monitor thermal environmental conditions for human occupancy.

Table 9 shows the chosen indicator with a short definition and the related source information.

Table 9 Thermal condition indicators

Variable Name	**SHORT-TERM**	**LONG-TERM**	**Evaluation**
Relative Humidity (RH)	yes	yes	The ratio of the partial pressure (or density) of the water vapor in the air to the saturation pressure (or density) of water vapor at the same temperature and the same total pressure. It is directly detected by humidity sensor embedded in BLE Beacons.
Air Temperature (AT)	yes	yes	The temperature of the air surrounding the occupant. It is directly detected by humidity sensor embedded in BLE Beacons.

4.4.2 House interaction indicators

Proximity sensors capture locational data by broadcasting an advertisement radio wave which is intercepted by a receiver located on a person. The distance between the sensor which emits the wave and the receiver is calculated using Received Signal Strength Indication (RSSI). As radio wave accuracy is highly dependent on environment, the RSSI is used to interpret distance from an advertising sensor and thus location is estimated based on proximity.

Environments using proximity for activity monitoring have several advantages over currently implemented remote activity monitoring devices [39]. Radio waves could determine intention and movement through increasing or decreasing proximity from a sensor to the receiving device as illustrated in Figure 5.

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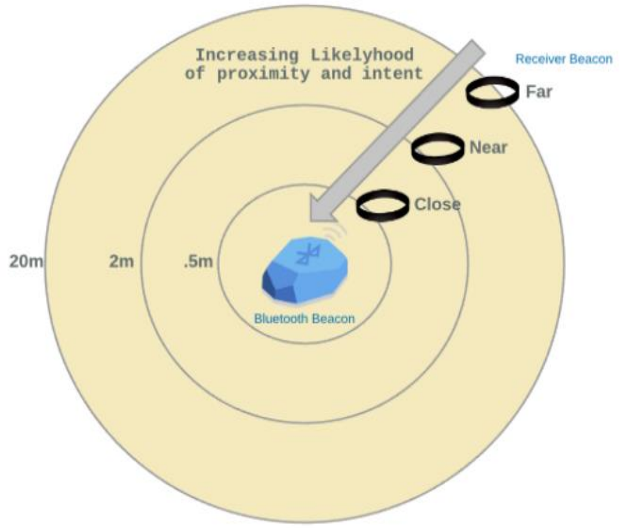

Figure 5 Proximity ranges from emitter to approaching receiver (picture taken from [39])

As RSSI grows stronger between a sensor and a receiver, locality, motion, intention and proximity can be determined (Kim et al., 2015). Multiple advertisement points could increase approximation within a home, and in NESTORE this aspect will be investigated starting from the collection of BLE RSSI by means of the wearable device (please refer to document D3.1 and D3.2 for additional details).

Interactions between the user wearing the BLE enabled device and Point of Interests (PoIs) in the user's home equipped with small battery-powered BLE Beacons will be used to infer indicators of sedentariness and rough estimation of high levels of Activities of Daily Living (ADLs) as outlined in Table 10. In particular, by placing BLE beacons throughout the user's homes, various rooms of the home will emit proximity radius. The user wearing a receiver would move between, stay sedentary or interact with objects in these radii. Another source of information for inferring interaction between the user and PoIs is represented by the accelerometer embedded in the BLE beacons. A threshold on the magnitude of the accelerometer's components will indicate if the furniture (e.g., doors, shutters, etc.) on which the beacon is attached is moving, thus identifying if the user has an interaction with the respective PoI.

Table 10 House interaction indicators

Variable Name	**SHORT-TERM**	**LONG-TERM**	**Evaluation**
Sedentary Level (SL)	no	yes	Movement through proximity ranges. It uses *Motion* over the long-time to detect *sedentary level*. The indicator will be personalised on the user environment and behaviour by means of a period of training (1 week).
Activities of Daily Living (ADLs)	yes	yes	It can be one of the set {Eating/Resting/Toileting) Immediate Proximity to Fridge, Microwave, Oven. Manipulation and Proximity to BLE equipped cabinets. Near Proximity to Bath.
Motion	yes	no	Number of movements between Proximity Beacons over time (daily).

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Abbreviations/Acronyms

6MWT
6 Minutes Wlaking Test, 17
AAL
Ambient Assisted Living, 11
ADLs
Activities of Daily Living, 30
AEE
Activity Energy Expenditure, 20
AT
Air Temperature, 29
AW
Awakenings, 12
BCG
Ballistocardiography, 11
BCT
Behaviour Change Technique, 24
BIA
Bioelectrical Impedance Analysis, 10
BLE
Bluetooth Low Energy, 25
BM
Bone Mass, 10
BMI
Body Mass Index, 10
BMR
Basal Metabolic Rate, 20
CFQ
Cognitive Failures Questionnaire, 21
COG-G
Cognition - Game, 23
CSD
Consensus Sleep Diary, 11
DEQ
Discrete Emotions Questionnaire, 24
DISE
Daily Inventory of Stressful Experience, 24
DRV
Dietary Reference Values, 18
DSS
Decision Support System, 5
EAR
Electronically Activated Recorder, 27
EI
Energy Intake, 20
FM
Fat Mass, 10
HAPA
Health Action Process Approach, 23
HRRec
Heart Rate Recovery, 16
HRV
Heart Rate Variability, 11
IAQ
Indoor Air Quality, 28
IDD
Interactions Duration, 27
IL
Interaction Location, 27
MDBF
Multidimensionaler Befindlichkeitsfragebogen (Multidimensional Mood Questionnaire), 24
MF
Memory Failures, 21
MHR
Maximal Heart Rate, 10
MS
Muscle Mass, 10
MSL
Medium Step Length, 10
PCS
Perceived Calm Sleep, 12
PoI
Point of Interest, 30
PPG
Photoplethysmography, 15
PSG
Polisomnography, 11
RFID
Radio Frequency IDentification, 25
RH
Relative Humidity, 29
RHR
Resting Heart Rate, 10
RPE
Rate of Perceived Exertion, 17
RSSI
Received Signal Strength Indication, 25
SE
Sleep Efficiency, 13
SI
Social Interaction, 26
SID
Social Interaction Detection, 26
SL
Sedentary Level, 30
Soff

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Appendix 1. Complete list of indicators

Table 11 Complete list of the extracted indicators with name, short-/long-term nature, type of source of information, and reference section where the indicator is explained

Indicator	Short-term	Long-term	Source	Ref.
Maximal Heart Rate (MHR)	no	Yes (baseline)	Hard	4.1.1.1
Resting Heart Rate (RHR)	no	no	Hard	4.1.1.1
Medium Step Length (MSL)	no	yes	Hard	4.1.1.1
Fat Mass (FM)	yes	yes	Hard	4.1.1.2
Total body water	yes	yes	Hard	4.1.1.2
Muscle mass	yes	yes	Hard	4.1.1.2
Bone mass	no	yes (baseline)	Hard	4.1.1.2
Body Mass index (BMI)	yes	yes	Hard	4.1.1.2
Perceived Calm Sleep (PCS)	yes	yes	Soft	4.1.1.3
Time in Bed (TIB)	yes	yes	Hard	4.1.1.3
Awakenings (AW)	yes	no	Hard	4.1.1.3
Sleep stages	yes	yes	Soft	4.1.1.3
Total Sleep Time (TST)	yes	yes	Hard	4.1.1.3
Sleep Efficiency (SE)	yes	no	Hard	4.1.1.3
Sleep onset (Son)	yes	no	Hard	4.1.1.3
Sleep offset (Soff)	yes	no	Hard	4.1.1.3
Sleep onset latency (SOL)	yes	no	Hard	4.1.1.3
Wake after sleep onset (WASO)	yes	no	Hard	4.1.1.3

Sleep quality index (SQI)	yes	yes	Soft	4.1.1.3
Non-structured Activity	yes	yes	Hard	4.1.1.4
Stairs	yes	yes	Hard	4.1.1.4
Sedentariness	yes	yes	Soft	4.1.1.5
Target Heart Rate Range (THR)	no	yes	Soft	4.1.2.2
Exercise target duration	no	yes	Hard	4.1.2.3
Exercise duration	yes	no	Hard	4.1.2.4
Exercise frequency	yes	no	Hard	4.1.2.5
Exercise heart rate	yes	yes	Hard	4.1.2.6
CardioResp score	yes	yes	Hard	4.1.2.7
Training adherence	yes	yes	Hard	4.1.2.8
Steps and distance	yes	yes	Hard	4.1.2.9
Pseudo-Six Minutes Walking Test (Pseudo-6MWT)	yes	yes	Hard	4.1.2.10
Elevation gain or Total ascent	yes	yes	Hard	4.1.2.11
Number of squat repetitions	yes	yes	Hard	4.1.2.12
Energy Consumption	yes	yes	Hard	4.1.2.13
Rate of perceived exertion	no	yes	Soft	4.1.2.14
Fatigue accumulation	yes	yes	Soft	4.1.2.15
Food Intake	yes	yes	Soft	4.2.1
Nutrient Intake	yes	yes	Soft	4.2.1
Number of meals	yes	yes	Soft	4.2.1

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Intake of supplements	yes	no	Soft	4.2.1
Refused Foods	yes	no	Soft	4.2.1
Basal Metabolic Rate (BMR)	yes	no	Soft	4.2.1
Activity Energy Expenditure (AEE)	yes	yes	Soft	4.2.1
Energy Intake (EI)	yes	yes	Soft	4.2.1
Total Energy Expenditure (TEE)	yes	yes	Soft	4.2.1
WM1-NB	no	Yes (baseline)	Soft	4.3.1
WM2-NU	Yes	Yes (baseline)	Soft	4.3.1
MF	Yes	Yes (baseline)	Soft	4.3.3
WM3-DSB	yes	no	Soft	4.3.3
WM1-NU	Yes	Yes	Soft	4.3.3
COG-G	yes	no	Soft	4.3.3
Cognitive activities	yes	no	Soft	4.3.3
HAPA	yes	no	Soft	4.3.4
MDBF	yes	yes	Soft	4.3.4
DEQ	yes	yes	Soft	4.3.4
Acute Stress	yes	no	Soft	4.3.4
Sentiment Valence	yes	no	Soft	4.3.4
SI	yes	no	Soft	4.3.5
Loneliness	yes	yes	Soft	4.3.5
Social interactions detection (SID)	yes	no	Hard	4.3.5

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Total number of interactions (TNI)	yes	yes	Soft	4.3.5
Interactions duration (IDD)	yes	yes	Hard	4.3.5
Interaction locations (IL)	yes	yes	Hard	4.3.5
Social activities	yes	no	Soft	4.3.5
Relative Humidity (RH)	yes	yes	Hard	4.4.1
Air Temperature (AT)	yes	yes	Hard	4.4.1
Sedentary Level (SL)	no	yes	Soft	4.4.2
Activities of Daily Living (ADL)	yes	yes	Soft	4.4.2
Motion	yes	no	Soft	4.4.2

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Appendix 2. Nutritional indicators - Example of indicators extraction, communication sequences, and technical details

In this Appendix, we show the technical details related to the extraction of nutritional indicators. We first show an example use case, then we present the communication paradigm to exchange data between the DSS and the module, finally we show some technical implementation aspect of the extraction module.

Example of *Food intake* and *Nutrient intake* indicators extraction

We present a complete example showing the way we calculate the nutrients per dish and a vision of the recommendations that can be shown. The data shown in Table 12, is needed to calculate the rates and necessity of nutrients of the user.

Table 12 User profile information needed for nutritional indicators calculation

Name and Surname	Gender	Date of birth	Weight (kg)	Height (m)	BMI (kg/m^2)
Juan García	Man	23/04/1945 = 73 years old	70	1,61	70/1,61^2= 27

1st step. Calculation of the Basal Metabolic Rate (Harris and Benedict equation)
The first step is to calculate the BMR, the energy that a person consumes to maintain their metabolic functions. In this case, as the profile of the example is a man, we apply the equation for Men as following:

MEN= [66,473 + (13,752 x W (kg)) + (5,003 x H(cm)) –(6,755 x A(years))]
BMR= 66,473 + (13,752×70) + (5,003×161) – (6,755×73)=
BMR= 66,473 + (962,64) + (805,483) – (493,115)= 1341,481kcal

2nd step. Calculation of the Total Metabolic Rate
Afterwards, we need to calculate the TMR, which has also into account the energy that needs to be intaken to be able to do the physical activity performed by the user:

TMR= 1341,481×1,55 = 2079,29555 ≈ 2080kcal/day
Physical Activity= Low = 1,55

Table 13 Physical activity factors per gender to calculate the Total Metabolic Rate (see D2.1.)

	Physical activity factors		
	Low	Medium	High
Men	1,55	1,78	2,10
Women	1,56	1,64	1,82

3rd step. Food detection and nutrients calculation
Taking the following example of 24 hours food intake, the nutrients are calculated:

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Table 14 Example of dishes intaken in 24 hours

Breakfast	Snack	Lunch	Snack	Dinner
Small cup of coffee (100ml)	A banana (100g)	Cod with potatoes: a) 1 codfish fillet (150g) b) ½ onion (70g) c) 1 potato (150g) d) olive oil (20g)	A cupcake (80g)	Omelette sandwich: a) 1 egg (65g) b) bread (60g) c) tomato (40g) d) olive oil (20g)

		Energy (per 100g)	Energy (kcal)	CHO (per 100g)	Carbohydrates (g)	F (per 100g)	Fat (g)	P (per 100g)	Protein (g)	Ca (per 100g)	Calcium (g)
BREAKFAST	**Small cup of coffe**										
coffee (ml)	100	2	2	0	0	0,18	0,18	0,12	0,12	2	2
SNACK	**A banana**										
banana (g)	100	89	89	20	20	0,3	0,3	1,2	1,2	9	9
LUNCH	**Cod with potatoes**										
codfish (g)	150	100	150	0	0	1,05	1,575	22,1	33,15	18	27
onion (g)	70	26	18,2	5,3	3,71	0	0	1,125	0,7875	25,4	17,78
potato (g)	150	206	309	46,06	69,09	0,1	0,15	4,29	6,435	34	51
olive oil (g)	20	887	177,4	0	0	99,9	19,98	0	0	0	0
SNACK	**A cupcake**										
cupcake (g)	80	387	309,6	39,9	31,92	22,4	17,92	6	4,8	25	20
DINNER	**Omelette sandwich**										
egg (g)	65	150	97,5	0	0	11,1	7,215	12,5	8,125	57	37,05
bread (g)	60	240	144	47	28,2	1,6	0,96	8,3	4,98	56	33,6
tomato (g)	40	19	7,6	3,5	1,4	0,1	0,04	0,9	0,36	11	4,4
olive oil (g)	20	887	177,4	0	0	99,9	19,98	0	0	0	0
		TOTAL	**1481,7**		**154,3**		**68,3**		**60,0**		**201,8**
				kcal	617,28		614,7		239,83		
				%	**41,66**		**41,49**		**16,19**		

where CHO=carbohydrates; F= Fat; P= Protein; CA = Calcium

According to the previous calculations, the total intake recorded corresponds to the following values:

Energy(kcal)	2+89+654,6+309,6+426,6=	**1481,8 kcal**
CHO (g)	0+20+72,8+31,92+29,6=	**154,32g**
F(g)	0,18+0,3+21,705+17,92+28,196=	**68,301g**
P(g)	0,12+1,2+40,3725+4,8+13,465=	**59,9575**
Ca(mg)	2+9+95,78+20+75,05=	**201,83mg**

		Energy of each macronutrient	Percentage of each macronutrient
Energy(kcal)	1481,8 kcal		
CHO (g)	154,32g	154,32×4*=617,28kcal	(617,28×100)/1481,8= 41,65%
F(g)	68,301g	68,301×9*=614,709kcal	(614,709×100)/1481,8= 41,48%
P(g)	59,9575g	59,9575×4*=239,83kcal	(239,83×100)/1481,8= 16,18%

*1g of CHO= 4kcal
*1g of F= 9kcal
*1g of P= 4kcal

4th <u>step. Evaluation of results and decision-making</u>

First of all, it must be pointed out that the example person doesn't cover their energy recommendations per one day which are 2080kcal/day, and he is just eating 1481,8 kcal, so an advice in order to increase the energy intake will be given.

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If we focus on the micronutrient calculated, calcium (Ca), the current intake is 201,84mg/day, a quantity that doesn't cover the recommendations for calcium intake established at the previous delivered paper (1200-1300mg/d).

In this case, an advice about calcium intake translated to a food group specific advice must be done. For example: ''A high amount of dairy products must be added for the next week → Try to add milk to your morning coffee or have a yogurt as a snack!''.

Use case of communication sequences

In this section, we show the main use case developed in the DSS Nutritional Analyser. In this case, the user uploads a photo of a dish and the system recognizes the dish correctly. The workflow in detail is depicted in Figure 6.

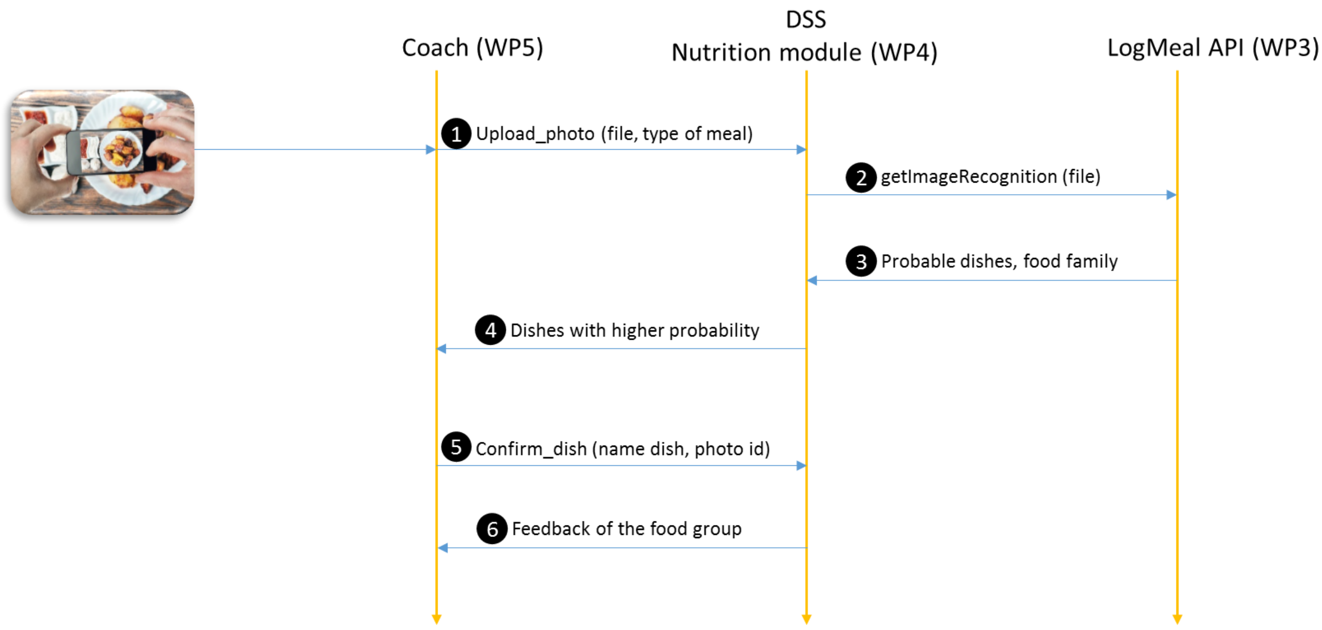

Figure 6 Communication sequence when a photo of a dish is uploaded.

1. **The user uploads a photo through the Coach specifying the type of meal (breakfast, lunch, snack or dinner).**
2. The DSS receives it and sends it to the LogMeal API.
3. The LogMeal API sends back to the DSS a response containing the most probable dishes with their probabilities, together with their food families.
4. The DSS sends to the Coach the dishes with higher probability.
5. User select one of the proposed dishes and the Coach confirm the dish sending the name of the dish and the photo id.

The DSS sends feedback of the food group related to the confirmed dish.

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Technical design of the Nutritional Indicators extraction module

The NESTORE system module named DSS Nutritional Analyser implements a set of RESTful web services used mainly by the Coach for retrieving detailed information ranging from the long-term (general trend) to the short-term detail (specific daily indicators) on various aspects as determined by the system.

Supported operations of the NESTORE

Operation	**Upload a photo to get food recognition**
URI	http://10.100.1.243:5000/dss/upload_photo
HTTP Request method	POST
Query Parameters	*file :* The image file in .jpg *meal:* The type of meal (breakfast, lunch, dinner, snack,drink) *userid:* The identification of the user (String)
Sample response	There are three types of response depending of the recognized image: - If type = "food", the JSON response will contain: ○ id: the identifier of the image. It will be used in other requests for identifying the photo ○ type: "food" ○ dish: an array containing the name of the recognized dishes with probabilities higher than 0.5 ○ foodType: recognized foodType and its probability Example: {"id": "5b0e882e8d169310ccd9533e", "type": "food", "dish": ["lentils_with_vegetables", 0.9870889782905579], "foodType": ["soup", 0.9907799363136292]} - If type = "drinks", the JSON response will contain: ○ id: the identifier of the image. It will be used in other requests for identifying the photo ○ type: "drinks" ○ drink: an array containing the name of the recognized dishes with probabilities higher than 0.5 Example: {"id": "5b39e5a98d16931260beb9b6", "type": "drinks", "drink": ["red wine", 0.9996318817138672]} - If type = "ingredients", the JSON response will contain: ○ type: "ingredients" ○ ingredient: recognized ingredient Example: {"type": "ingredient", "ingredient": "tomato"} - If it is not recognized as food the response will be: {"type": "non_food"}

Operation	**Modify type (when recognized type is wrong)**
URI	http://10.100.1.243:5000/dss/modify_type
HTTP Request method	POST
Query Parameters	photoid : The id contained in the response of the request "upload_photo" *realType:* The real type of the photo (food, drinks, ingredients, non_food) *userid:* The identification of the user (String)
Sample response	{"id": "5b39f8d08d16931260beb9b8", "type": "drinks", "drink": ["white coffee", 0.732984721660614]}

Appendix 3. Preliminary Assessment of Social Indicators

The following appendix presents some ongoing activities and data collection initiatives, with the goal of assessing the indicators described in Section 4.3.5 for detecting and measuring the social interactions.

We first present a preliminary architecture useful for collecting and analysing the sensing information, then two meaningull experimental settings with the goal of showing how to effectively collect, store and analyse data in real-world indoor environments.

A Distributed Analytics Platform

The NESTORE project requires to collect data from a number of pilot sites with heterogeneous features. We are designing a distributed sensing architecture for collecting, storing and analysing data gathered along the time. Figure 7 shows the prototype designed so far.

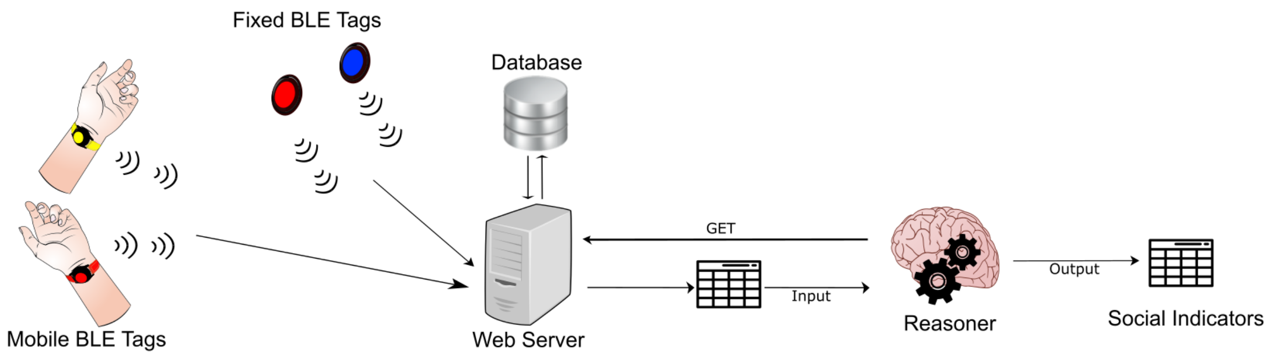

Figure 7 An overview of the sensing architecture for social interactions

The architecture comprises three building blocks:

1. sensing units
2. web server
3. reasoner

The **sensing units** are based on the BLE technology (Bluetooth Low Energy) useful for detecting interactions among people. Specifically, FLEX is designing a custom wristband equipped with a BLE unit able both to send and receive BLE signals up to a specific range (e.g. 0 - 5 meters away). In this way, a NESTORE user wearing the wristband can record BLE signals emitted by other NESTORE users in the nearby and it can send BLE signals to other NESTORE users. Not only, but wristbands can also collect data from BLE units deployed on fixed locations (e.g. living room, courtyard, kitchen and every aggregation spot), so that to reveal where interactions happen more frequently.
Wristbands send all the data captured (both from other users and from fixed locations) to a **Web Server** which stores the data received. Finally, data will be analyzed by a **reasoner** which, periodically, retrieves the data stored and it analyses them with the goal of:

- detecting the meaningful social interactions of every NESTORE user
- computing the social indicators

In order to detect the social interactions of NESTORE users, we plan to implement and test the SID algorithm (Social Interaction Detection). SID will rely on the observation that RSS (Received Signal Strength) indicators of BLE signals change while users have meaningful face-to-face meetings. More precisely, when users A and B

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meet, the RSS of their BLE signals changes remarkably. Figure 2 shows an example during which A and B meet for 5 times in a period of 30 minutes. This example has been obtained from the SocializeME data collection campaign, described in Section 4.3.5.

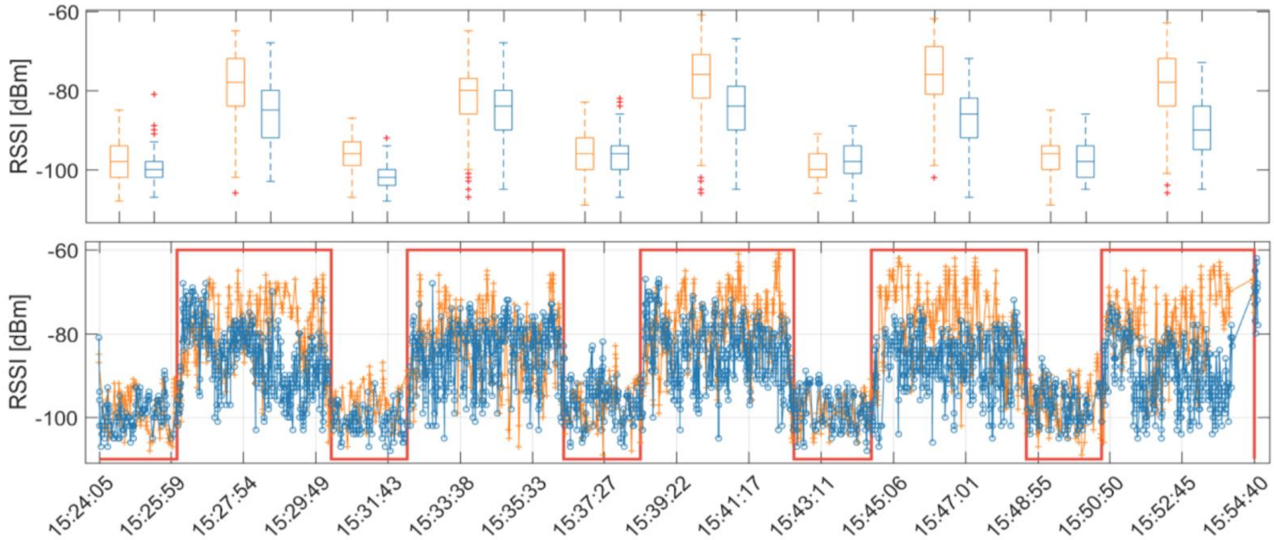

Figure 8 RSS variation during face-to-face meetings.

The low part of Figure 8 shows, in red, the time intervals during which A and B had a real face-to-face meeting (the ground truth), while on orange and blue colours we show the RSS values captured by commercial BLE wristbands. From the figure, it is clear that meetings are characterized by higher values of RSS with respect to non-meetings periods. SID will exploit such observation, with the goal of detecting, for ever NESTORE user, those time intervals during which RSS values changes significantly. It is worth to notice that RSS values are strongly affected by several conditions: obstacles, humidity, body posture as well as electromagnetic interferences. All of such conditions contributed to increase the complexity of detecting features of the RSS values. The top part of Figure 1 shows how A hears BLE signals from B, and how B hears signals from A. From the figure it is clear that the two users do not receive BLE signals with sale values, rather we observe significant variations.

Pleliminary Results from the social indicators

The SID algorithm has been tested and the results are presented in [40]. This research is conducted in the framework of SocializeME project, aimed at studying social dynamics among students of a high school.
In this work, we investigated the possibility of detecting social interactions among individuals by using their personal mobile phones, as BLE beacon receivers, and commercial BLE Tags, as BLE beacon transmitters. Relying on commercial devices and not on ad-hoc expensive devices, we experienced several drawbacks and we consider this work as a representative case-study of the hidden complexities behind the detection of human interactions. As an example, we observed a remarkable and variable loss rate of the expected beacons; the heterogeneity of Bluetooth chipset causes significant differences in the quality of the received signals; variations related to the wearing position of the smartphones (e.g., in front or back pocket, in a hand, or on a desk), the body orientation of the volunteers and the presence of other people in the nearby impact on the detection accuracy. We performed a preliminary calibration campaign of the algorithm based on real experiments conducted with students of I.T.I.S. E. Fermi high-school located in Lucca, Italy. The calibration campaign consisted of several round of tests during which we recruited volunteer students from different classes. We built a dataset of interactions obtained by reproducing accurate tests combined with a diary of the ground-truth of such interactions. Each test has been repeated for 5 runs, where each run lasted for 6 minutes,

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of which 2 minutes of non-interaction and 4 minute of interaction. We included several kinds of tests in the test plan, according to common ways of using and *wearing* a smartphone: (1) smartphones placed in the front pocket and (2) smartphones placed in the back pocket, standing or sitting face-to-face. After each test, the volunteers filled in the ground-truth diary, in which they reported: the start time of the interaction, the end time of the interaction and, if any, remarks about the test. At the end of the calibration campaign, we collected 300 interaction tests from 20 different dyads.

We started our analysis by considering the two algorithm parameters, namely p and τ_{rssi}, presented in the evaluation of SID variable in Table 8. They establish the number of valid beacons to be considered for the opening and closing conditions. For each test, we measured accuracy and F-score while varying both p and τ_{rssi}. Since we cannot assume a priori the way the individuals use and *wear* their smartphones, we combined the results of all the tests, providing an overall performance assessment of the algorithm in terms of accuracy and F-score. Accuracy is defined as:

$$Accuracy = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}}$$

and assesses the proportion of correct answers of the algorithm with respect to the total amount of observations. TP, TN, FP, and FN are the true positive, true negative, false positive and false negative, respectively, considering correct predictions are true and wrong predictions as false. F-score combines both precision $P = {}^{TP}/_{(TP + FP)}$ and recall $R = {}^{TP}/_{(TP + FN)}$, as follows:

$$F - score = 2 * \frac{\mathrm{P} * \mathrm{R}}{\mathrm{P} + \mathrm{R}}$$

Figure 9 reports the overall results. The first observation watching the figure is that both accuracy and F-score increase as τ_{rssi} increases to reach the maximum value around a specific value. After such threshold, both curves decrease.

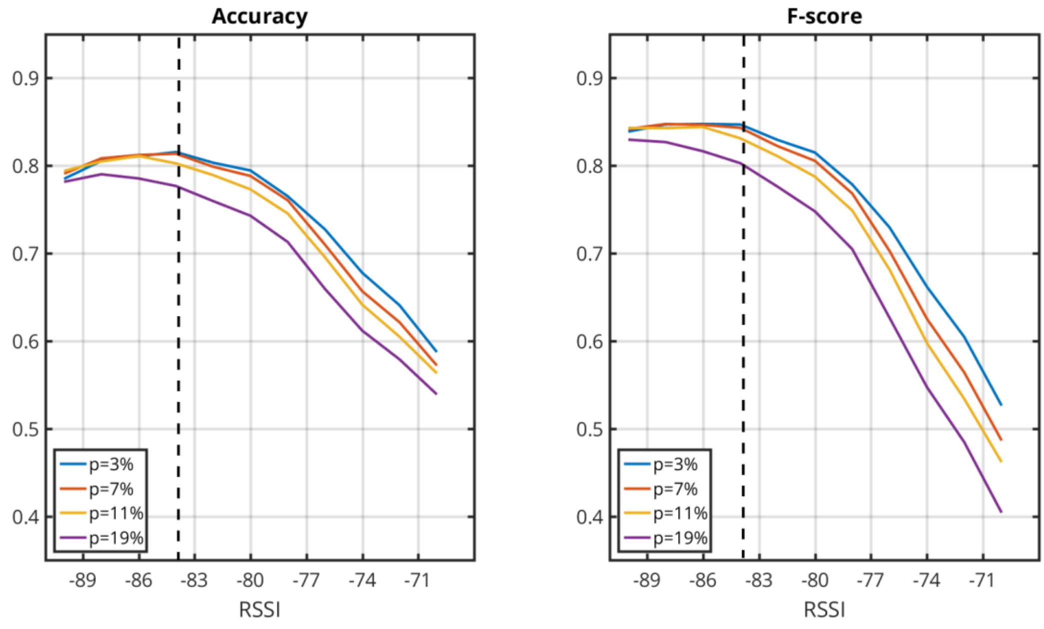

Figure 9 Accuracy and F-score for all the performed tests

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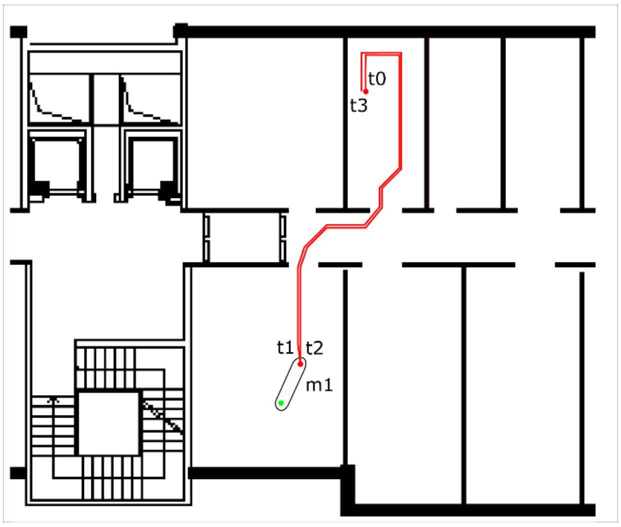
The optimal tuning is obtained for the following values:

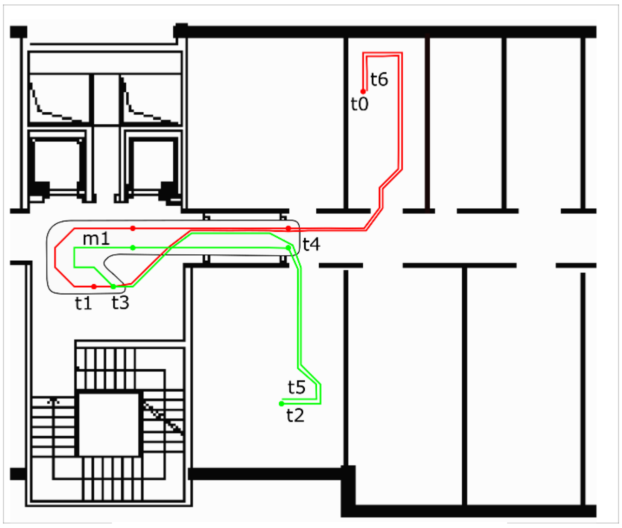
$\hat{p}$=3%, $\hat{\tau}$=−84 dBm

which provide an overall accuracy of 81.56% and F-Score of 84.7%. The presented results demonstrate the effectiveness of the proposed SID algorithm, which needs to be recalibrated by using the devices provided for the NESTORE framework.

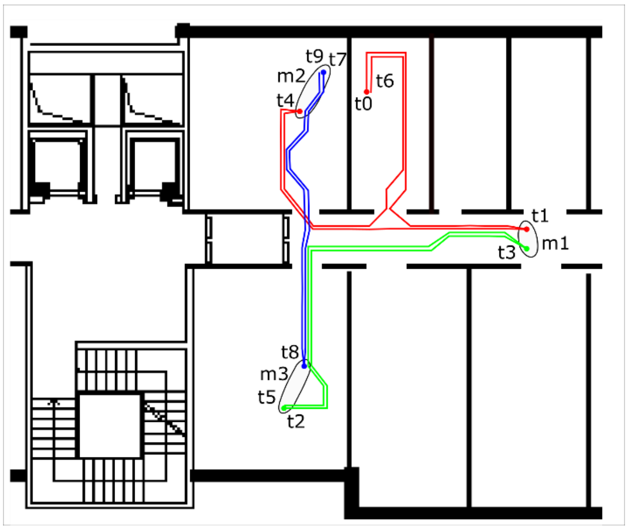
Moreover, we built a dataset with the purpose of providing a large number of RSSI values, obtained from fixed and wearable BLE tags, that can be used to test solutions operating with different configurations (e.g., self/remote positioning and direct/indirect positioning) and a large number of use cases, including social interactions among users. The dataset [41] is freely accessible for research purposes without any limitation.



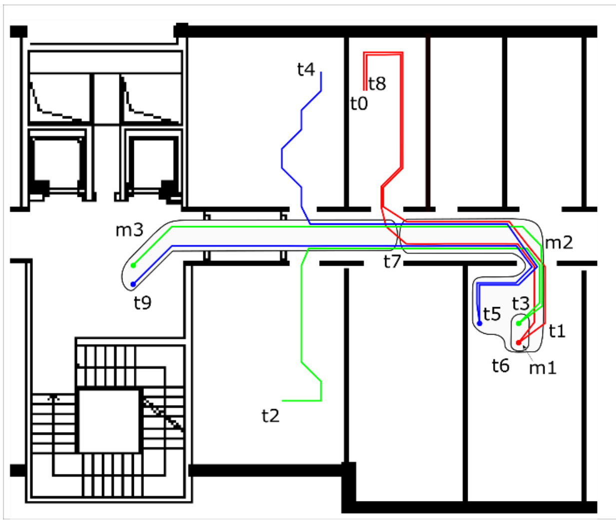
(a) Scenario “Social 1”



(b) Scenario “Social 2”



(c) Scenario “Social 3”



(d) Scenario “Social 4”

Figure 10 The four social interactions scenarios.

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The dataset was produced by monitoring up to three human “actors” that act and move in a portion of our building, National Council of Research (CNR) located in Pisa (Italy), that includes offices, corridors and public spaces. Each actor carried two devices, a BLE tag on the chest as beacons transmitter and a smartphone in the hand as receiver of the signal from any other transmitting device.

The experimental campaign for the social interactions scenarios was split in four sessions, involving different numbers of actors. In particular, we selected two scenarios with two actors (Scenario “Social 1” and scenario “Social 2” in
Figure 10) and two scenarios with three actors (Scenario “Social 3” and scenario “Social 4” in
Figure 10).

Figure 10 also shows the actors’ paths indicated with different colours: red (actor 1), green (actor 2), and blue (actor 3). In the first scenario, actor 1 moves at time t0 in order to meet actor 2 fixed in his position. At time t1, the meeting m1 begins and it ends at time t2 when actor 1 goes back to his room (
Figure 10a). In the second scenario (
Figure 10b), the same two actors meet (meeting m1) in the coffee area at time t3 and walk together in the corridor until time t4 and then go back to their respective offices. Finally, scenarios 3 and 4 involved three actors. In the third scenario, three different meetings involving two actors were performed (
Figure 10c), while in the fourth scenario, different kinds of meetings involving two and three actors were performed (
Figure 10d).

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