D4.1: State-of-the-art, requirement analysis, and initial specification of the Holistic Behaviour Analysis Framework

Dissemination level: Public

Document type: Report

Version: 1.0.1

Date: February 28, 2018 (original)

March 5, 2019 (this version)

This project has received funding from the European Union's Horizon 2020 research and innovation programme under Grant Agreement #769553. This result only reflects the author's view and the EU is not responsible for any use that may be made of the information it contains.

Document Details

Project Number	769553
Project title	Council of Coaches
Title of deliverable	State-of-the-art, requirement analysis and initial specification of the Holistic Behaviour Analysis Framework
Due date of deliverable	February 28, 2018
Work package	WP4
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Reviewer(s)	Alvaro Fides (UPV)
Approved by	Coordinator
Dissemination level	Public
Document type	Report
Total number of pages	50

Partners

- University of Twente – Centre for Monitoring and Coaching (CMC)
- Roessingh Research and Development (RRD)
- Danish Board of Technology Foundation (DBT)
- Sorbonne University (SU)
- University of Dundee (UDun)
- Universitat Politècnica de València, Grupo SABIEN (UPV)
- Innovation Sprint (iSPRINT)

Abstract

This deliverable (D4.1) represents the contribution of the Work Package 4 (WP4) to the first crucial milestone (M6) of the Council of Coaches project. The main aim of D4.1 is to define the initial specifications and designs of the Holistic Behaviour Analysis Framework (HBAF). In order to present the initial concept of the HBAF, the sensing and profiling approach is elaborated based on a thorough investigation of the state-of-the-art sensing technologies. Hence, a literature review on sensing technologies is provided, focusing on on-body and off-body sensors in order to sense, identify and quantify the user's physical, emotional, cognitive, and social behaviour. Furthermore, a requirement analysis for the initial design of the HBAF is described explaining the functional and non-functional requirements elicited from a technical point of view. Finally, the system's specification for the initial design of the HBAF are presented through use cases.

Corrections

v1.0.1	Correctly applied EU logo on header page.
	Changed UPMC to Sorbonne University (SU).

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Symbols, abbreviations and acronyms

ACC	Accelerometer
API	Application Programming Interface
AVC	Accelaration Vector Changes
AU	Action Unit
CMC	Centre for Monitoring and Coaching
COUCH	Council of Coaches
D	Deliverable
EC	European Commission
ECG	Electrocardiogram
FACS	Facial Action Coding System
FFT	Fast Fourier Transform
FR	Functional Requirement
GPS	Global Positioning System
GSD	Gait Segment Detection
GSR	Galvanic Skin Response
HBAF	Holistic Behaviour Analysis Framework
HCI	Human-Computer Interaction
ID	Identifier
kNN	k-Nearest Neighbour
M	Month
Max	Maximum
Min	Minimum
MS	Milestone
NA	Not Available
NFR	Non-Functional Requirement
PC	Personal Computer
PPG	Photoplethysmography
RF	Random Forest
RMS	Root Mean Square
RMSE	Root Mean Square Error
RRD	Roessingh Research and Development
SDK	Software Development Kit

SMS	Short Message Service
std	Standard Deviation
SU	Sorbonne University
SVM	Support Vector Machine
WP	Work Package
UC	Use Case
UDI	Unique Device Identifier
UUI	Unique User Identifier
UPV	Universitat Politècnica de València
UT	University of Twente

1 Introduction

"Council of Coaches" (COUCH) revolves around the concept of multi-party virtual coaching, where a number of domain-specific virtual characters or e-coaches interact with each other and with the user to inform, motivate and discuss about health and well-being related issues (e.g. physical, cognitive, emotional, and social well-being). Individual coaches will listen to the user, ask questions, inform, discuss among themselves, jointly set personal goals and inspire the users to take control over their health and well-being. Any combination of specialised council members collaboratively covers a wide spectrum of lifestyle interventions, with a particular focus on age-related impairments, chronic diseases, and Diabetes Type 2.

The Council of Coaches project will combine smart multimodal sensing technologies to seamlessly and opportunistically measure and model the user behaviour in a comprehensive fashion, including physical, cognitive, mental and social aspects. This holistic sensing and modelling approach not only aims at registering, analysing and inferring each determinant of behaviour in a user-centric manner but also mining the interactions among users and with their physical and virtual environment.

The Council of Coaches project involves three main approaches; sensing and profiling, dialogue management and user interaction. The aim of this report is to emphasise on the sensing and profiling approach and present the initial concept of the holistic behaviour analysis framework. Specifically, the main objectives of this technical component are described in Section 2, while the different terminologies and definitions are elaborated on in Section 0. Furthermore, state-of-the-art sensing technologies, are presented in Section 4, which will contribute to the sensing modalities of the Holistic Behaviour Analysis Framework. Finally, the initial design of the system, including the requirement analysis and specification, is described in Section 5.

2 Objectives

The aim of this deliverable (D4.1) is to develop the initial specifications for the Holistic Behaviour Analysis Framework, concerning the first crucial milestone of the Council of Coaches project. Additionally, four other technical components will be delivered at the same time (M6 – February 2018), where initial user and stakeholder analysis will be performed. The result of this phase of the project is documented in the following series of five deliverables:

- D2.2: Report on user and stakeholder needs and expectations [**Stakeholder Analysis**]
- D3.1: Initial coaching strategies and knowledge base [**Shared Knowledge Base**]
- D4.1: State-of-the-art, requirement analysis and initial specification of the Holistic Behaviour Analysis Framework (*this deliverable*) [**Behaviour Analysis Framework**]
- D5.1: Dialogue and Argumentation Framework Design [**Dialogue Framework**]
- D6.1: Requirements and Concepts for Interaction Mobile and Web [**HCI Design**]

The overall strategy for the user-centred design and innovation process in the project is an iterative approach with rapid development and evaluation of three main prototypes and a final technical demonstrator. We strongly believe that the most valuable user input can be obtained from the evaluation of *working prototypes*. Hence, the first prototype deliverable is scheduled for an early release on M9 (May, 2018), allowing us to start the process of collecting concrete feedback from our users.

In order to achieve the delivery of a first prototype in M9, and due to the innovative nature of the project, multiple design and requirements elicitation trajectories are initiated simultaneously. Broadly speaking, the project initiates a "technology push" and "market pull" strategy simultaneously, as depicted in Figure 1.

This deliverable, depicted as "(Holistic) Behaviour Analysis Framework" in Figure 1, contributes to the technology push factors of the design and requirements phase, in line with the deliverable's three main objectives.

Objective 1: To provide a literature review on state-of-the-art sensing technologies using on-body and off-body sensors in order to sense, identify and quantify the user's physical, emotional, cognitive, and social behaviour.

Objective 2: To elaborate a requirement analysis for the initial design of the Holistic Behaviour Analysis Framework.

Objective 3: To develop the system's specifications for the initial design of the Holistic Behaviour Analysis Framework.

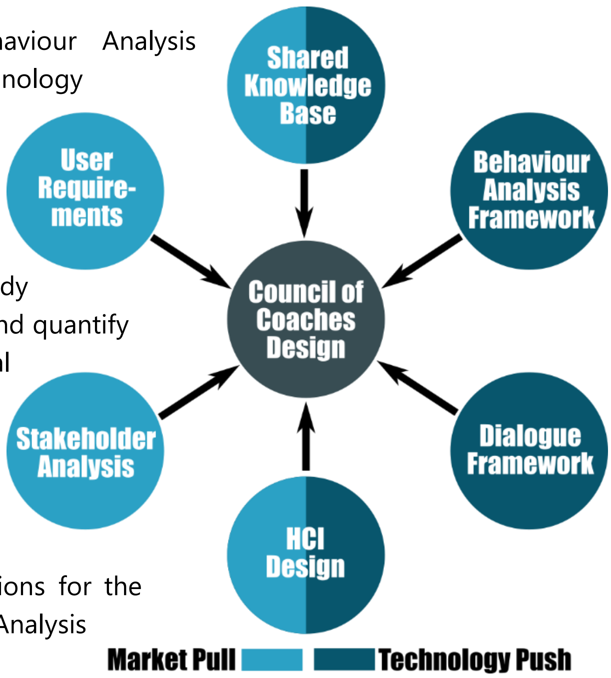

Figure 1: Global design and requirements elicitation process in the Council of Coaches project focusing on a simultaneous market pull and technology push strategy.

3 Behaviour Analysis Framework Terminology

In Table 1 we report and describe on a number of key terms that are used throughout this report. At the moment of delivery of this document there are ongoing efforts in the project to align the use of terminology between the different technical components. As such, these definitions will hold up for the scope of this deliverable but are subject to modification in the course of the project.

Table 1: An overview of the mentioned terms in this report, as well as their definition, is presented.

Term	Definition
Wearable devices or wearables	Electronic devices that can be conveniently worn on the body and that can measure explicit/implicit human actions (e.g., smartwatches or smartphones)[1]
Non-wearable devices	Any electronic device that cannot be worn on the body and that can measure explicit/implicit human actions (e.g., laptop)
On-body sensors	Sensors embedded into or available on wearable devices (e.g., smartphone's accelerometer)
Off-body sensors	Sensors embedded into or available on non-wearable devices (e.g., laptop's microphone)
Physical Behaviour	Range of human bodily movements such as physical activities (e.g., walking, standing, sitting), transitions (e.g., sitting-to-standing), and hand movements (e.g., eating a sandwich, hand waving)
Cognitive Behaviour	Range of mental actions/states related to perception, attention, memory, language skills, visuospatial processing, and executive function (e.g., reading or problem solving)
Emotional Behaviour	Range of mental actions/states related to mood (e.g., happiness, sadness)
Social Behaviour	Range of communicative interactions that take place through physical (e.g., face-to-face) and virtual (e.g., social networks, phone calls) means
Short-term behaviours or primitives	Physical, emotional, social or cognitive behaviours that last less than a certain period of time (normally in the order of hours/days)
Long-term behaviours or routines	Physical, emotional, social or cognitive behaviours that last more than a certain period of time (normally in the order of weeks/months)

[1] "Smartphones might not be worn on the body in the same way as a wristwatch, jewellery or spectacles, but they are in our pockets and handbags. Whether we're "wearing" the computer on our body or just have it to hand seems a rather unimportant distinction in the larger scheme of things. For all intents and purposes smartphones are considered wearables." (O'Dwyer, 2017)

4 State-of-the-Art Behaviour Sensing Technologies

As described in Section 2, the first objective of this deliverable is to provide a review of state-of-the-art sensing technologies, which will serve as the principal generator of knowledge on the user's short and long-term behaviours. This knowledge will provide relevant background information for improving the user-coach interaction and supporting the dialog and argumentation process with objective and continuous behaviour-related contents.

Thus, this section focuses on elaborating the state-of-the-art systems used in literature for extracting valuable information from smartphones and smartwatches, including unobtrusive on-body sensors (e.g. accelerometer, gyroscope, GPS, number of phone calls, duration of smartphone usage, etc.) but also off-body sensors (e.g., microphone, camera, etc.) related to the interaction of the user with the Council of Coaches interface. Hence, two different approaches for sensing are presented in the following subsections.

4.1 On-Body Sensing

This subsection focuses on sensing technologies based on on-body data acquisition through wearables. Wearable technology with embedded sensor systems, such as smartphones and smartwatches, is gaining more and more popularity, enabling new potentials for monitoring people's health. In 2016, there were 2.1 billion of smartphone users worldwide, while this number is expected to rise to 2.5 billion by 2020 (Helbostad, et al., 2017). Similarly, smartwatches have grown in popularity and affordability during the last years and their sales are forecast to reach 141 million units in 2018 (Statista, 2018). Consequently, smartphones have been the most popular wearable devices, followed by smartwatches and other wrist-worn devices.

The decision of focusing on smartphones and smartwatches as on-body sensing devices, instead of other commercially available wearable devices, was taken due to their preference from users but also due to the different types of data that can be acquired. On-body sensors include motion sensors that can track the motion, orientation and position of the user's body, bio-signal sensors that provide information about physiological parameters such as user's heart rate, skin conductivity and respiration rate, but also sensors that provide information related to the user-smartphone interaction such as screen-(un)locks or text typing. Thus, smartphones represent sensors that are not firmly attached to the body (they can be placed on bags and backpacks or they can be worn on trousers' and shirt's pocket), while smartwatches represent wrist-worn sensors firmly attached to the body.

4.1.1 Smartphone Monitoring

The recent technological advances enabled the release of smartphone devices with powerful specifications and enormous sensing possibilities. Thus, these devices have been increasingly used in healthcare and behavioural research in order to collect health data, monitor patient's vital signs and deliver comprehensive healthcare information to practitioners, researchers and patients, by enhancing the ability to diagnose and track diseases (Silva, et al., 2015).

Consequently, the main aim of this subsection is to elaborate on the sensing modalities that a smartphone device can offer to measure behaviour and health-related data. Four sensing modalities exploited to date in off-the-shelf smartphones, including activity, cognitive, emotional, and social sensing, are presented in the following subsections.

4.1.1.1 Physical Activity Sensing

The research on human's physical activity recognition has gained much attention during the recent years as an essential descriptor of human behaviour. For more than two decades, researchers have intensively explored the use of inertial sensors, such as accelerometers and gyroscopes (Helbostad, et al., 2017) (John & Freedson, 2012), to fairly quantify physical activity in epidemiological, surveillance, and intervention medicine (Buman, et al., 2010) (Copeland & Esliger, 2009) (Patterson, et al., 1993). These devices fundamentally consist of an accelerometer, a small inertial sensor that records the movement of the body where the device is placed (e.g. wrist, arm, chest, hip, thigh, etc.). Smartphones, which natively incorporate these types of inertial sensors, have been studied for estimating human's physical activity in both controlled and uncontrolled settings (Hekler, et al., 2015). The use of mobile phones as stand-alone physical activity monitors has been explored during the last decade, as a technological follow-up of traditional accelerometer-based mechanisms. The first systems on physical activity monitoring through mobile phones were based on simple pedometers and step counters building on the acceleration measured through the built-in sensors (Garcia, Hang, Sarela, & Karunanithi, 2010) (Mladenov & Mock, 2009). However, the use of more sophisticated machine learning techniques has enabled the extraction of more meaningful data for activity detection (Shoaib, et al., A Survey of Online Activity Recognition Using Mobile Phones, 2015). For example, sedentary, ambulatory and commuting activities have been successfully identified in (Kwapisz, Weiss, & Moore, 2011) (Lau & David, 2010) (Martín, Bernardos, Iglesias, & Casar, 2013) (Sun, et al., 2010). Furthermore, the detection of more complex physical behaviours, including housework and other everyday activities, has also been proven feasible in a number of works (Adil Mehmood, Ali, Asad Masood, & Teemu, 2014) (Ouchi & Doi, 2012). Activity recognition systems based on inertial sensor data are shown to be dependent on the specific location and placement of the sensors (Banos, Damas, Pomares, & Rojas, 2012) (Banos, Toth, Damas, Pomares, & Rojas, 2014). These limitations have been overcome in a number of works by either exploiting the use of location-independent features (Sun, et al., 2010) (Han, Bang, Nugent, McClean, & Lee, 2014) (Han, Vinh, Lee, & Lee, 2012) or identifying in the first place the actual location of the smartphone to use a customised activity identification model (Guiry, Karr, van de Ven, Nelson, & Begale, 2014).

Mobile phones have not only been used to detect body movement and orientation but also to identify abnormal physical behaviour, and especially gait (Isho, Tashiro, & Usuda, 2015) (Martín, Bernardos, Iglesias, & Casar, 2013) (Mazilu, et al., 2012) (Yamada, et al., 2012), fall (Abbate, et al., 2012) (Dai, et al., 2010) (Mehner, Klauck, & Koenig, 2013) (Mulcahy & Kurkovsky, 2015), movement transitions (Bieber, et al., 2010) (Mellone, Tacconi, & Chiari, 2012) and postural instability or balance (Lee, Kim, Chen, & Sienko, 2012) (Patterson, Amick, Thummar, & Rogers, 2014) (Wai, Duc, Syin, & Zhang, 2014). Furthermore, gesture detection through mobile phones have been studied for rehabilitation of the knee (Ferriero, et al., 2013), hand (Algar & Valdes, 2014) or shoulder (Shin, et al., 2012) among other body parts. Specific activities of daily relevance such as sleeping have also been inferred by analysing mobile phone usage patterns (DeMasi, et al., 2017) (Lane, et al., 2014). The monitoring of people's location and mobility patterns has represented a paramount topic in mobile computing since its early days. (Phithakkitnukoon, et al., 2010) mentioned that GPS sensors have been possibly the primal source for mobility analysis. Despite their widespread use, the accuracy of these sensors has been quite limited in indoor settings, where the connection between mobile phone and satellites is normally lost. Accordingly, researchers proposed some alternate options to track the location of users indoor. One of the most effective ones is the so-called pedestrian dead reckoning (PDR), a path integration process based on calculating one's current position by using a previously determined position. The mobile phones built-in accelerometers, gyroscopes and magnetometers are normally used to this end (Kang & Han, 2015) (Pratama, Widyawan, & Hidayat, 2012) (Tian, Zhang, Zhou, & Liu, 2014). Some other approaches elaborate on the analysis of call logs for tracking the mobility of a user or group of users (Oliver, Matic, & Frias-Martinez, 2015). Consequently, it is possible to detect the location and the user's current physical activity outdoors,

through accelerometer and GPS traces for example, but also indoors through Wi-Fi and Bluetooth signal strength (Burns, et al., 2011) (Gravenhorst, et al., 2015).

Table 2: Summary of physical activity sensing using smartphones.

Authors	Sensors	Features	Classifiers	Behaviours	Condition
(Garcia, Hang, Sarela, & Karunanithi, 2010)	3-axis ACC	raw ACC	linear regression analysis (accuracy: 98%)	counting steps	cardiovascular disease patients
(Kwapisz, Weiss, & Moore, 2011)	3-axis ACC	average, std, average absolute difference, average resultant acceleration, time between peaks, binned distribution	multilayer perceptron (accuracy: 91.7%)	physical activities, including: walking, jogging, ascending/descending stairs, sitting, and standing	healthy
(Lau & David, 2010)	3-axis ACC	mean and std of raw ACC, mean and std of FFT of ACC	kNN (accuracy: 99.6%)	physical activities, including: walking, standing, sitting, and ascending/descending stairs	healthy
(Sun, et al., 2010)	3-axis ACC	mean, variance, energy, frequency-domain entropy and correlation among axes of raw ACC and magnitude ACC	SVM (F-score: 93.1%)	physical activities, including: stationary, walking, running, bicycling, ascending/descending stairs and driving	healthy
(Burns, et al., 2011)	ACC, GPS, Wi-Fi, Bluetooth	raw data	decision trees (accuracy: 60.3%)	location and activity intensity (light, moderate, vigorous)	depressive patients
(Abbate, et al., 2012)	3-axial ACC	max and min value of magnitude, peak duration, activity ratio, free-fall index and step count	neural network architecture (accuracy: 82%)	fall detection	healthy elders
(Martín, Bernardos, Iglesias, & Casar, 2013)	Y,Z-axis ACC, Y,Z-axis magnetometer, gravity, light and proximity	mean and variance	decision table (accuracy: 88%)	gait analysis (walking slow, fast, normal) and physical activities including running, sitting and standing	healthy
(Yamada, et al., 2012)	3-axial ACC	peak frequency, autocorrelation peak, coefficient of variance	multivariate analysis (not specified)	gait analysis	rheumatoid arthritis
(Lane, et al., 2014)	3-axial ACC and ambient audio (microphone)	time and frequency domain, including mean, variance, energy, entropy and correlation among axes	naïve classifier (accuracy: 80%)	sleep patterns and activity (stationary, walking, running)	healthy

Authors	Sensors	Features	Classifiers	Behaviours	Condition
(Wai, Duc, Syin, & Zhang, 2014)	gravity (based on 3-axial ACC)	sway area per second, mean distance and mean velocity (both in medial lateral and anterior-posterior directions) based on orientation	unknown classifier (accuracy: 92%)	body balance	healthy
(Isho, Tashiro, & Usuda, 2015)	3-axial ACC	autocorrelation coefficient, harmonic ratio and interstride variability	univariate logistic regression analysis (performance: 75%)	gait analysis with risk of falling	chronic stroke
(Mulcahy & Kurkovsky, 2015)	3-axial ACC	magnitude	(not specified)	fall detection	healthy
(DeMasi, et al., 2017)	3-axial ACC	8 features including: average and std of the magnitude of acceleration and the dominant frequency; entropy of the normalised power spectrum, etc.	logistic regression (averaged accuracy: ~80%)	sleep duration (through contiguous series of user's inactivity)	healthy

4.1.1.2 Cognitive Sensing

Cognitive sensing is possibly the most challenging task since there is not a smartphone sensor that can easily measure cognition-related processes. Humans' cognitive functions can be divided into six main categories, including perception, attention, memory, language skills, visuospatial processing and executive functioning, which can be monitored by assessing the performance at specific tasks (Schmidt, Collette, Cajochen, & Peigneux, 2007). Specifically, the attentional system of a user can be evaluated by assessing the user's alertness, which modulates sensory, motor, and cognitive processing (Van Dongen & Dinges, 2005). For instance, fatigue, a diminished state of alertness and attention, can be related to motor vehicle accidents and other occupational mistakes (Dinges, 1995). Thus, cognitive performance can vary significantly during the day and among different users, and can be affected by multiple individual factors, such as the need to sleep at a specific time and based on the body clock or by user's social obligations.

(Abdullah, et al., 2016) showed that alertness can oscillate approximately 30% depending on time and body clock type (circadian rhythms), while other factors such as the daylight saving time (practice of advancing clocks during summer), hours slept, and stimulant intake can influence alertness as well. For instance, a high level of alertness was noticed in their study when participants checked their phones more frequently and only for shorter periods of time, while low levels of alertness were noticed when participants engaged in more sustained use. On the other hand, (Pijnenborg, et al., 2010) studied the use of SMS text messages to compensate for the effects of cognitive impairments in subjects with schizophrenia.

It is also possible to track user's behaviour and cognitive state by evaluating the screen touch events while using a smartphone device. Specifically, data on screen touches can be used to evaluate the speed and the responses time to smartphone surveys in order to track short term cognitive states, such as attention and alertness (Abdullah, et al., 2016) (Torous, Kiang, Lorme, & Onnela, 2016). Additionally, screen touch patterns can be employed to detect quality metrics, sleeping duration and when the subject uses the phone during night-time, leading to the monitoring of long-term cognitive states in many mental disorders, such as schizophrenia (Torous, Kiang, Lorme, & Onnela, 2016) and depression (Gravenhorst, et al., 2015).

Table 3: Summary of cognitive sensing using smartphones.

Authors	Sensors	Features	Classifiers	Behaviours	Condition
(Pijnenborg, et al., 2010)	SMS text messages	(not specified)	logistic multi-level modelling (not specified)	perception and motivation	psychotic disorder patients (such as schizophrenia)
(Abdullah, et al., 2016)	screen status and self-reported sleep diaries	local time, internal time, sleep duration, relative sleep need, phone usage burstiness, mean duration of phone usage sessions, average time between phone usage sessions, and frequency of short phone usage sessions	L1 linear regression (RMSE: 11.39%)	alertness	healthy
(Torous, Kiang, Lorme, & Onnela, 2016)	GPS, 3-axial ACC, phone call and text message logs, Wi-Fi, Bluetooth, audio, phone and screen status	raw data	(not specified)	attention	psychiatric and neurological disorders (such as schizophrenia)

4.1.1.3 Emotional Sensing

There is a great number of studies using smartphone technologies for detecting emotional states and mood disorders. Most of these studies focus on different mental disorders, such as depression, bipolar disorder or borderline personality disorder, among others. The most common way to detect emotional states on a smartphone is based on collecting user's self-reported data through an application, sometimes also including cognitive and physical behavioural states (Gravenhorst, et al., 2015). For instance, MONARCA (Bardram, et al., 2013) is a therapeutic application for bipolar disorder patients using a simple questionnaire through a smartphone device for self-reporting user's mood score.

Smartphone devices can also be used to automatically sample data for the monitoring and treatment of many mental disorders. Specifically, assumptions can be made about the subject's current mood through statistical analysis of some mobile sensing modalities, such as variations in phone usage patterns, texting and calling (Gravenhorst, et al., 2015). For instance, an unusual increased number of outgoing phone calls could be related to a change in the mental state of patient. (Muaremi, et al., 2014) examined the phone call parameters and showed that the phone call duration and the accumulated talking time can

be used to predict bipolar disorder episodes, significantly. Furthermore, many studies focus on audio and voice recognition methods in order to extract user's mood and detect short-term emotional behaviour through sound and phone call features. Examples of phone call features are the number of calls, the number of involved ID phone callers, and the sum, average and standard deviation length of calls (Grunerbl, et al., 2015). Sound features consist of speech and voice features acquired through phone's microphone, including for example features related to phone call interaction (e.g., the average speaking length and duration) and audio recordings (detect emotions based on user's voice) (Grunerbl, et al., 2015). (Vanello, et al., 2012) used speech signals to extract voice features related to pitch and pitch changes, combined with acquired ECG signals from external device, in order to characterise the mood of bipolar patients to depressive, hypomanic and euthymic state.

Another category of smartphone applications that run quietly in the background, without demanding an active request information from the user, is this for monitoring SMS messages. (Tausczik & Pennebaker, 2010) studied the content of SMS messages, using classification tools to scan the words from a SMS text and interpret it to psychologically meaningful terms for estimating the subject's emotions and mood. Similarly, (Rutland, Sheets, & Young, 2007) studied the mood modification and the addictive attitudes towards SMS, by analysing the number of sent and received SMS messages.

Additionally, other smartphone sensing modalities such as GPS, accelerometer and Wi-Fi signal strength, most frequently used for physical activity sensing, can also provide here valuable information about the patients' state (Gravenhorst, et al., 2015). (Lomranz, Bergman, Eyal, & Shmotkin, 1988) showed that the outdoor behaviour of patients is related to their mental states. (Gravenhorst, et al., 2015) explained that depressed patients can be isolated into their rooms, spending most of the time in bed, while manic patients tend to travel long distances in an unusual way. Similarly, (Osmani, et al., 2013) found that the activity level of bipolar patients is related to their mental state; a reduced activity level could be interpreted as a depressed episode, while an enhanced activity level could indicate the beginning of a manic episode. (Burns, et al., 2011) the Mobilyze! system for patients with depression, sampling data from the accelerometer, GPS, Bluetooth, Wi-Fi, ambient light and phone usage analytics in order to target depression by detecting user's location and emotional states, such as sadness, happiness, anger and anxiety.

Similar to the ongoing research on detecting the different mental states through a smartphone device, there are many studies focusing on the recognition of emotional states, such as happiness and boredom, as well. (Pielot, Dingler, Pedro, & Oliver, 2015) developed a more sophisticated machine learning approach to automatically identify user's boredom situations from mobile phone usage, context and demographics. Other emotional states such as happiness have been found to be detectable through the analysis of mobile phone data (Muaremi, Arnrich, & Troster, 2012). (Bogomolov, Lepri, & Pianesi, 2013) used an extensive set of indicators obtained while using a mobile phone, such as call logs, SMS and Bluetooth proximity data, plus environmental (mainly weather) data and personality traits, which can be intelligently combined to estimate people's daily happiness.

The use of these applications enables medicine prescription, where the psychiatrists have access to the patients' database, being able to continuously adjust the prescriptions (Gravenhorst, et al., 2015). Thus, the psychiatric is able to involve and adjust the medicine on time, when the patient goes from a depressed to a manic state for example, by monitoring the short-term emotional behaviour. Moreover, physical activity levels measured through the smartphone's acceleration sensors and GPS traces have been proved adequate for psychiatric assessment of depression, when long-term data series over a period of days or weeks are considered (Gravenhorst, et al., 2015) (Osmani, et al., 2013).

Table 4: Summary of emotional sensing using smartphones.

Authors	Sensors	Features	Classifiers	Behaviours	Condition
(Burns, et al., 2011)	ACC, GPS, Wi-Fi, Bluetooth, ambient light	raw	regression tree with poor performance (not specified)	states such as sadness and depression	depression patients
(Vanello, et al., 2012)	microphone (combined with ECG from external device)	average pitch, jitter and pitch std	customised algorithm based on a spectral matching approach (not specified)	depressive, hypomanic and euthymic states	bipolar patients
(Bogomolov, Lepri, & Pianesi, 2013)	phone activity (including call/SMS logs and Bluetooth logs), weather conditions and personality traits	amount and diversity of call/SMS and proximity, user active behaviours and regularity in user behaviours	RF (accuracy: 80.81%)	daily happiness	healthy
(Muaremi, et al., 2014)	microphone	phone call statistics, including: number of phone calls, sum, average, min, max and std of phone calls' duration; speaking cues, including: speaking length and other similar non-verbal activities cues; voice features, including range and std of pitch frequency, kurtosis energy, mean of mel-frequency cepstral coefficients	RF (F1-score: 82%)	manic and depressive states	bipolar patients
(Grunerbl, et al., 2015)	microphone	phone call features including: the number of phone calls, the number of involved ID phone callers, and the sum, average and std length of calls; sound features including: the average speaking length, duration, etc.	naïve Bayes (accuracy: 69% or 76% combined with ACC and GPS features)	depressive and manic states	bipolar patients
(Pielot, Dingler, Pedro, & Oliver, 2015)	microphone and phone status	number of phone calls, time of last phone call and SMS, battery level, etc	RF (accuracy: 83%)	boredom	Healthy

4.1.1.4 Social Sensing

Social networking sites, such as Twitter and Facebook, have been used to study users' social behaviour through computers, smartphones and tablets. Users actions, posts, comments and sentiments have been examined in order to extract useful information through the internet regarding their mood but also their social activity and interaction with other users (Lachmar, 2017) (Xu, et al., 2018) (Zengin Alp & Gündüz Öğüdücü, 2018). Additionally, there is an ongoing research on sampling social behaviour data through smartphone devices, especially focusing on the correlation of social inactivity with many mental disorders. (Burns, et al., 2011) developed the Mobilyze! system for patients with depression in order to detect user's location and measure the interaction level with friends. They sampled data for emotional but also for social sensing, using sensors such as accelerometer, GPS, Wi-Fi, Bluetooth and other parameters from phone usage. (Frost, et al., 2013) studied the number of ingoing and outgoing phone calls and text messages in order to detect short term social behaviour and detect the current mood of patients. For instance, mentally ill patients tend to get talkative in a manic phase (Gravenhorst, et al., 2015), while a low level of social interaction is correlated with depression (George, Blazer, Hughes, & Fowler, 1989).

Furthermore, (Lane, et al., 2014) measured social isolation based on the total duration of ambient conversations, by using the mobile phone microphone. (Moturu, et al., 2011) studied the Bluetooth proximity detection to estimate the sociability level of people and predict their mood. (Vu, et al., 2015) proposed the use of Bluetooth scans, photo captures and audio recording among other features to get better traces of the user movement. It is also possible to estimate commuters' mobility in predefined regions, by using the cell phone ID, timestamp, and location data of an event (e.g., call, SMS, Internet usage). This information can also be used to estimate population distribution, segregation outside the home, types of activities carried out in different parts of the city or geographic context of subjective well-being (Calabrese, Ferrari, & Blondel, 2014) (Palmer, et al., 2013). Co-location and communication sensors have been proven of much utility to characterise the change in proximity, face-to-face interactions, and individual trajectories in the contagion and propagation of diseases (Madan, et al., 2012) (Vazquez-Prokopec, et al., 2013).

Mobile devices can be also used to measure long-term behavioural cues and social signals and reveal relevant determinants of health. For example, the analysis of aggregated and anonymised call records captured from the mobile phone infrastructure is sufficient to characterise human behaviour in dense areas (Vieira, Frias-Martinez, Oliver, & Frias-Martinez, 2010) and during critical events such as natural disasters (Pastor-Escuredo, et al., 2014).

Table 5: Summary of social sensing using smartphones.

Authors	Sensors	Features	Classifiers	Behaviours	Condition
(Burns, et al., 2011)	ACC, GPS, Wi-Fi, Bluetooth, ambient light, phone usage (phone calls, applications activity, etc)	raw	regression tree (not specified)	social interaction and social isolation	depression patients
(Moturu, et al., 2011)	Bluetooth	signal detection and strength	(not specified)	social interaction and social isolation	healthy
(Lane, et al., 2014)	microphone	duration of phone calls	linear regression (accuracy: 56%)	social isolation	healthy

4.1.2 Smartwatch Monitoring

Mobile health (mHealth) has emerged as a promising field in treating patients with smartphones, since they come with inbuilt sensors and computing and communication resources that allow to track individual's behaviour and activity, unobtrusively. However, despite the enormous sensing abilities that a smartphone can offer, there are some sensing modalities that require the sensors to be firmly attached to the body. For instance, activity behaviour understanding is not always accurate when the sensors are not firmly attached to the body, since motion signals can get distorted by any movement of the device. In contrast, smartwatches have the potential to accurately identify a large variety of activities, including hand-based and eating-based activities that cannot be effectively recognised by smartphones. Additionally, smartwatches allow us to measure physiological signals, such as galvanic skin response (GSR), respiration signals and skin temperature.

This subsection elaborates on the sensing modalities that a smartwatch device can offer to measure behaviour and health-related data, focusing on the four sensing modalities that are presented in the following subsections.

4.1.2.1 Physical Activity Sensing

The recent technological advances in wearable technology enhanced the research on activity recognition by using wrist-worn devices. Many studies focus on wrist-worn activity recognition, either using multimodal wearables, such as smartphones combined with smartwatch devices, or using data from one single device, such as smartwatch or wrist-worn activity tracker. (Weiss, et al., 2016) showed that smartwatches as a standalone device have the potential to accurately identify a large variety of everyday activities, such as walking, jogging, climbing stairs, sitting, standing, but also more complicated hand-based activities that cannot be effectively recognised by smartphones (e.g. handwriting, clapping, brushing teeth, eating sandwich). (Shoaib, et al., 2016) studied the use of wrist-worn devices, which were emulated by placing smartphones at the wrist position, in order to detect activities such as walking, jogging, biking, walking on stairs, sitting, standing, eating, typing, writing, drinking coffee, giving a talk and smoking. They focused on accelerometer, linear acceleration, which can be obtained by removing acceleration due to gravity from accelerometer measurements, and gyroscope data. Furthermore, they compared the performance of wrist-worn devices with smartphones placed on user's pocket and they found that combining data from wrist and pocket-worn devices outperforms the wrist-worn devices.

There is a significant number of studies that focus on activity recognition using only accelerometer data from wrist-worn devices, trying to detect everyday activities (Chernbumroong, Atkins, & Yu, 2011) (Gjoreski, Gjoreski, Luštrek, & Gams, 2016) (Yang, Wang, & Chen, 2008). Additionally, there are studies on tremor (Wile, Ranawaya, & Kiss, 2014), steps count detection (Ahanathapillai, Amor, Goodwin, & James, 2015), gait analysis (Cola, Avvenuti, Musso, & Vecchio, 2017), fall detection (Gjoreski, Gjoreski, Luštrek, & Gams, 2016), eating behaviours analysis (Alexander, et al., 2017) (Kalantarian & Sarrafzadeh, 2015) (Thomaz, Essa, & Abowd, 2015) and sleeping stages (Boletsis & McCallum, 2016). Most of these studies focus on short-term activity behaviour, trying to estimate real time prediction, while only a few studies explore longer time frames. (Thomaz, Essa, & Abowd, 2015) evaluated a smartwatch based system in order to detect food intake gestures and identify the eating moments in 60 minutes time window segments. Furthermore, (Garcia-Ceja, Brena, Carrasco-Jimenez, & Garrido, 2014) focus on recognising complex and long-term activities, such as working, eating and shopping. Specifically, they used accelerometer data in order to map a sequence of simple (short-term) activities to more complex (long-term) activities. However, there are some limitations on defining the precise number of segments for long-term activities, since a complex activity might not be always composed by the same distribution of simple activities and also the variability in their execution among individuals. (Phan, Siong, Pathirana, & Seneviratne, 2015) estimated the sleep quality based on heart rate and accelerometer recordings, but also, they evaluated the performance of smartwatch optical heart rate sensor compared to ECG and PPG

devices. Short-term sleep monitoring contains information about sleep stage, heart rate variability and movements during sleep. On the other hand, long-term sleep monitoring provides deeper understanding of numerous behaviours and disorders. For instance, sleep apnoea can lead to cognitive impairments and influence subject's emotions, since the lack of sleep can make the subject feel more fatigue, affecting the attention and alertness (cognitive behaviour).

Table 6: Summary of physical activity sensing using smartwatches.

Authors	Sensors	Features	Classifiers	Behaviours	Condition
(Yang, Wang, & Chen, 2008)	3-axis ACC	mean, correlation between axes, energy, interquartile range, mean absolute deviation, root mean square, std, and variance	neural network (accuracy: 95%)	walking, running, scrubbing, standing, working at a PC, vacuuming, brushing teeth, and sitting	healthy
(Chernbumroong, Atkins, & Yu, 2011)	3-axis ACC	mean, min, max, std, variance, correlation between axes, difference between axes, spectral energy, spectral entropy	decision tree (accuracy: 94.13%)	sitting, standing, lying, walking, and running	healthy
(Garcia-Ceja, Brena, Carrasco-Jimenez, & Garrido, 2014)	3-axis ACC	mean, variance, correlation between axes; & mean, variance and average derivative of the magnitude	hidden markov model (accuracy: 97.9%)	shopping, showering, eating, working, commuting, and brushing teeth	healthy
(Wile, Ranawaya, & Kiss, 2014)	3-axis ACC	tremor peak frequency, peak power, and power of the first four harmonics	not specified (Cohen's kappa: 61%)	tremor	Parkinson disease
(Ahanathapillai, Amor, Goodwin, & James, 2015)	3-axis ACC	(not specified)	(not specified)	worn-state, activity level and step count detection	healthy
(Kalantarian & Sarrafzadeh, 2015)	microphone audio	skewness, mean distance between peeks, zero crossings, quartile 2&3	RF (F-score: 94.5%)	apple and potato chip bites, water swallows, talking, and ambient noise	healthy
(Phan, Siong, Pathirana, & Seneviratne, 2015)	3-axis ACC, PPG	mean, std	(not specified)	sleep quality	healthy
(Thomaz, Essa, & Abowd, 2015)	3-axis ACC	mean, variance, skewness, kurtosis, RMS	RF (F-score: 76.1%)	eating activities, including food intake gestures (fork-knife, spoon and hand) & eating moments	healthy
(Boletsis & McCallum, 2016)	3-axis ACC, body temperature, ambient temperature and GSR	(not specified)	(not specified)	sleep stages (REM, light, and deep sleep), sleep duration and quality	healthy elders

Authors	Sensors	Features	Classifiers	Behaviours	Condition
(Weiss, et al., 2016)	3-axis ACC and 3-axis gyroscope	average, std, average absolute difference, average resultant acceleration, time between peaks, binned distribution	RF (accuracy for ACC: 70% and accuracy for gyroscope: 57.5%)	not hand-oriented activities: walking, standing, sitting, ascending/descending stairs, jogging hand-oriented activities: typing, handwriting, clapping, brushing teeth, eating, drinking	healthy
(Shoaib, et al., 2016)	3-axis ACC & 3-axis gyroscope	mean, std, min, max, semi-quartile, median and the sum of first ten FFT coefficients (based on axes and magnitude)	naïve Bayes, kNN and decision tree using (F-score: performance varies per activity)	walking, jogging, biking, walking on stairs, sitting, standing, eating, typing, writing, drinking coffee, giving a talk and smoking	healthy
(Gjoreski, Gjoreski, Luštrek, & Gams, 2016)	3-axis ACC	mean, absolute mean, area, absolute area, variance, skewness, kurtosis, mean crossing rate, correlation, amplitude	RF (accuracy: 72%)	cycling, walking, standing, lying, sitting, running, kneeling, bending and transitions	healthy
(Gjoreski, Gjoreski, Luštrek, & Gams, 2016)	3-axis ACC	acceleration vector changes (AVC)	RF (accuracy: 85%)	fall detection	healthy
(Alexander, et al., 2017)	3-axis ACC and 3-axis gyroscope	mean, median, skewness, variance, std, zero crossing rate, kurtosis, linear acceleration	naïve Bayes (sensitivity: 89%)	eating activities, including cooking, eating a meal and cleaning dishes	type 2 diabetes
(Cola, Avvenuti, Musso, & Vecchio, 2017)	3-axis ACC	mean, median, skewness, RMS, mean crossing rate (MCR) and average absolute acceleration variation (AAV)	gait segment detection (GSD) customised algorithm (average performance: 95.5%)	gait detection	healthy

4.1.2.2 Cognitive Sensing

Since the release of smartwatch devices, there have been many ongoing studies on the treatment of chronic conditions and diseases, using smartwatch devices as intelligent cognitive assistance technologies. Their aim has been to improve people's everyday life, focusing on older adults and on patients suffering from dementia whose memory, thinking, language, understanding and judgment abilities are compromised (Prange & Sonntag, 2016). (Prange & Sonntag, 2016) studied the development of dialogues for mental healthcare applications, by using automatic speech recognisers and text-to-speech synthesis through smartwatches. (Ciabattoni, et al., 2017) proposed a smartwatch based system to record physiological signals, such as heart rate, GSR and body temperature in order to detect mental stress during cognitive tasks, in real time. For instance, an increase of user's GSR level can be related to mental stress due to cognitive effort. (Torrado, Gomez, & Montoro, 2017) developed a pervasive assistance system, based on the acquired physiological and motion signals of a smartwatch, in order to assist people with autism spectrum disorders and behavioural issues through customised emotional self-regulation strategies. Following the provided instructions from caregivers to patients, the proposed

system detects the user's inner state and displays the self-regulation strategies, when the user's heart rate exceeds the configurable threshold. Moreover, (Lee, Lee, & Chung, 2015) used smartwatches to measure driver alertness according to two classes; awake and drowsy. Specifically, they used accelerometer and gyroscope data to detect the driver steering wheel movement, and PPG signals (through a photoplethysmography sensor that transmitted data through Bluetooth) to monitor the driver chronic physiological state in real time. Additionally, (Boletsis & McCallum, 2016) studied a gaming system on smartwatches for cognitive screening and sleep duration assessment of elders trying to detect short terms cognitive skills and sleep duration/stages with the purpose of predicting cognitive decline in a long-term base and requesting relevant treatment through medical experts.

Table 7: Summary of cognitive sensing using smartwatches.

Authors	Sensors	Features	Classifiers	Behaviours	Condition
(Lee, Lee, & Chung, 2015)	3-axial ACC, 3-axial gyroscope and PPG	17 in total; based on time, spectral context and phase space domain	mobile-based SVM (accuracy: 95.8%)	driver alertness (awake and drowsy)	healthy
(Boletsis & McCallum, 2016)	interaction with cognitive screening game	(not specified)	(not specified)	cognitive screening and assessment of sleep duration and quality	healthy elders
(Prange & Sonntag, 2016)	microphone audio and text	(not specified)	(not specified)	spoken dialogue for mental applications through automatic speech recognisers and text-to-speech synthesis	dementia
(Ciabattoni, et al., 2017)	heart rate, GSR and body temperature	27 features including mean, std and max	kNN (accuracy: 84.5%)	mental effort and stress	healthy
(Torrado, Gomez, & Montoro, 2017)	3-axis ACC, 3-axis gyroscope, 3-axis compass, PPG and barometer	(not specified)	(not specified)	awareness and emotion self-regulation	autism spectrum disorders (ASD)

4.1.2.3 Emotional Sensing

Smartwatch data have been also used to assess mood and personal well-being. (Ciabattoni, et al., 2017) used smartwatches to record physiological signals, such as heart rate, GSR and body temperature in order to detect emotional states, such as relax or mental stress, in real time. For instance, an increase of user's GSR level could not only indicate a wide range of emotional and psychological states, such as the experience of joy, fear, anger or even anxiety, but can be also related to mental stress due to cognitive effort. Similarly, (Egilmez, et al., 2017) studied motion, GSR and heart rate signals acquired through a smartwatch device in order to detect stress in college students. Furthermore, (Zhu, et al., 2016) developed a system for mood inference using a fusion of motion, location, and temporal signals collected from smartwatch devices. They estimated the user's mood based on the performed activities and they detected if the person was happy, relaxed or tired. (Kamdar & Wu, 2016) developed the PRISM (Passive, Real-time Information for Sensing Mental Health) platform, using activity, motion, light and

heart rate data from a smartwatch, in order to monitor mental health and detect user's states of happiness, energy and relaxation.

Table 8: Summary of emotional sensing using smartwatches.

Authors	Sensors	Features	Classifiers	Behaviours	Condition
(Kamdar & Wu, 2016)	3-axis ACC, heart rate, light intensity rates and text entries	1658 features, including key press and latency statistics	RF and gradient boosted regressor trees (not specified)	happiness, energy and relaxation	healthy
(Zhu, et al., 2016)	3-axis ACC	(not specified)	regression (performance: 60.52%)	activity and emotional states, including happy, relaxed or tired	healthy
(Ciabattoni, et al., 2017)	heart rate, GSR and body temperature	27 features including mean, std and max	kNN (accuracy: 84.5%)	states such as relax and stress	healthy
(Egilmez, et al., 2017)	3-axis ACC and gyroscope, heart rate, GSR	110 features, including mean, max, min, std, skewness, kurtosis	RF with minute-based classification (F-score: 88.8%)	stress detection	healthy

4.1.2.4 Social Sensing

Apart from using smartphones, social behaviour data can be studied using smartwatch devices, too. (Ferrari, Puccinelli, & Giordano, 2015) developed a gesture based authentication system through smartwatches. The authors used Bluetooth and accelerometer data to detect whether two users have shaken hands and award soft authentication privileges in order to exchange data (instead of gaining access though password). Bluetooth is particularly used here to locate neighbour devices, while accelerometer data can be used to detect handshaking, with three main identifiable states: pre-handshake, handshake and post-handshake. However, this could also be an option for identifying social interactions among users, based on the detection of handshaking gestures. (Kytö & McGookin, 2017) mentioned that is also possible to detect whether the subjects want to end their conversation and leave by constantly checking their smartwatch during the conversation, which can be translated into signs of social isolation when prolonged over longer periods of time.

Table 9: Summary of social sensing using smartwatches.

Authors	Sensors	Features	Classifiers	Behaviours	Condition
(Ferrari, Puccinelli, & Giordano, 2015)	3-axis ACC and Bluetooth	mean, variance, min, and max	memory neural network (accuracy: 97%)	hand shaking gesture	healthy

4.2 Off-body Sensing

Apart from using unobtrusive on-body sensors, it is possible to detect human behaviour based on other sensors available in everyday devices that the user may encounter during the interaction with the council of coaches (e.g., smart TVs, laptops or the like). Hence, this subsection focuses on the extraction of relevant information through audio and video processing approaches in order to detect behavioural events.

Human affect can be described in terms of discrete (basic) emotional categories that include happiness, sadness, fear, anger, disgust, and surprise. However, a discrete list of emotions fails to describe the range of emotions that occur during interactions. An alternative way to describe is using a dimensional description. The most widely used representation of affective state is in terms of dimensions of evaluation (valence) and activation (arousal) (Cowie, et al., 2001). Some studies also use an additional dimension, dominance (Grimm & Kroschel, 2005). Evaluation (valence) measures how humans feel, from positive to negative and activation (arousal) measures whether humans are more or less likely to take an action under the emotional state, from active to passive. The necessity to have human-centred designs and interfaces in the computing domain has given rise to a growing research domain in automatic analysis of human affective behaviour (Zeng, Pantic, Roisman, & Huang, 2009). A summary of the works in affect recognition and the modalities used is presented in this section and a detailed survey of the same can be found in (Cowie, et al., 2001) (Pantic & Rothkrantz, 2003) (Vinciarelli, Pantic, & Bourlard, 2009) (Zeng, Pantic, Roisman, & Huang, 2009).

There exists a strong association between affect and audio and visual signals (Russell, Bachorowski, & Fernandez-Dols, 2003). Speech conveys affective information through explicit (linguistic), and implicit (paralinguistic) messages. Pitch, energy, and speech rate are some of the basic-emotion-related prosodic features extracted from the audio signal (Harrigan, Rosenthal, & Scherer, 2005). Audio data has been used to detect affective states (i.e., positive, negative, neutral) in (Chul Min & Narayanan, 2005) (Neiberg, Elenius, & Laskowski, 2006). Facial display is a natural means of communicating emotions (Pantic & Rothkrantz, 2003). Facial Action Coding System (FACS) has been widely used in recognition of basic emotions and complex psychological states. Audio-visual affect recognition has been carried out to recognise basic emotions and research is underway to detect additional non-basic emotions.

4.2.1 Audio data

In this section, some of the existing tools, that can be used for socio-emotional analysis by extracting features from the audio-visual data, will be presented.

A. **openSMILE**: This is a feature extraction tool used to extract large audio feature sets in real-time. A configuration file can be used to interconnect feature extractor components easily. The input is the speech instances (.wav format) and output file with the extracted features is saved as a specific file format, Attribute-Relation File Format (ARFF). It is written in C++ and is available as both a standalone command line executable as well as a dynamic library. In contrast to large scale feature sets, which have been successfully applied to many speech classification tasks (Valstar, et al., 2014), smaller, expert-knowledge based feature sets have also shown high robustness for the modelling of emotion from speech (Ringeval, et al., 2014). Some recommendations for the definition of a minimalistic acoustic standard parameter set have been recently investigated, and have led to the Geneva Minimalistic Acoustic Parameter Set (GEMAPS) and to an extended version (EGEMAPS) (Eyben, et al., 2016). The acoustic low-level descriptors (LLD) cover spectral, cepstral, prosodic and voice quality information. The feature sets can be used to train models to classify emotions from audio data.

B. **openEAR**: The open Emotion and Affect Recognition Toolkit can be used for automatic emotion recognition from speech (Eyben, Wöllmer, & Schuller, 2009). It is based on the openSMILE feature extractor. It provides algorithms for audio feature extraction which is implemented in C++, classifiers, and pre-trained models on well-known emotion databases. Also, scripts and tools are provided to quickly build and evaluate custom model sets.

C. **OpenVokaturi**: It is an emotion recognition tool that can be easily integrated into existing software applications (Vokaturi, 2018). Several libraries in C and Python are available for integration of emotion detection into applications. Happiness, sadness, anger, fear and neutrality are the emotions recognised. The presence and/or intensity of each of these emotion

is denoted with a value between 0 and 1, which represents the weight of that emotion over the whole emotions.

D. **EmoVoice**: It is a framework for real-time recognition of emotions from acoustic properties of speech (Vogt, André, & Bee, 2008). The steps involved are, detection speech segments, extraction of features and training a classifier model. Once a model has been trained it can be used to classify emotional speech in real-time. It has been integrated as toolbox into the Social Signal Interpretation framework. It facilitates the linking of the output to applications and thus allows affective interface implementations.

4.2.2 Video data

A. **openFACE**: It is an open source tool intended for facial landmark detection, head pose estimation, facial action unit recognition, and eye-gaze estimation (Baltrušaitis, Mahmoud, & Robinson, 2015). AUs are the fundamental actions of individual muscles or groups of muscles. The tool offers two kinds of scores for the AUs i.e., intensity and presence. The former provides the intensity of 17AUs on a continuous value scale from 1 (minimally present) to 5 (present at maximum intensity) with a score of 0 indicating absence. The latter indicates the presence or absence of 18AUs (provides an additional AU28). The features extracted can be used for emotion detection.

B. **Affectiva**: It classifies facial expression detected, based on FACS (Kaliouby, 2018). It utilises twenty facial points to identify seven emotions i.e., joy, sadness, disgust, contempt, anger, fear, and surprise. Other than the basic emotions it can also predict gender, age, ethnicity, valence, and engagement. It is available as SDK to detect emotions in real time on a device or as an API to analyse recorded data on cloud.

C. **Kairos**: It provides face detection, identification and verification, emotion, age, gender, sentiment, ethnicity and multi-face detection, attention measurements and face grouping (Belyeu, 2018). It can be accessed via API/SDK. Although there is a free version for personal use with access to all the features the SDK is not free.

D. **Fubi**: It is a framework for full body interaction using a depth sensor such as the Microsoft Kinect or the Asus Xtion and provides gesture and posture recognition (Kistler & Andre, 2015). It is written in C++ and additionally includes a C# wrapper. It is able to recognise four gesture categories i.e., static postures (configuration of several joints), linear/angular movements, combination of postures and movements, and symbolic gestures (gesture with complex shape).

Table 10: Summary of existing audio and video tools for off-body sensing.

Name	Sensor	Features	Behaviours	Remarks
EmoVoice (Vogt, André, & Bee, 2008)	audio	spectral, cepstral, prosodic and voice quality	joy, satisfaction, anger, frustration	free availability
openEAR (Eyben, Wöllmer, & Schuller, 2009)	audio	spectral, cepstral, prosodic and voice quality	joy, sadness, disgust, anger, fear, and surprise.	free availability
openSMILE (Ringeval, et al., 2014)	audio	spectral, cepstral, prosodic and voice quality	(not specified)	free availability
openFace (Baltrušaitis, Mahmoud, & Robinson, 2015)	video (facial)	facial landmark detection, head pose estimation, facial action unit recognition, and eye-gaze estimation	(not specified)	free availability
Fubi (Kistler & Andre, 2015)	video (body)	static postures, linear/angular movements, combination of postures and movements, and symbolic gestures	arms crossed, hands in/near pockets, hands down together, swiping/pushing, wave right/left hand, bowing, head nod, head shake etc.	free availability
Affectiva (Kaliouby, 2018)	video (facial)	facial landmarks estimation, head orientation estimation, interocular distance, facial action unit recognition	joy, sadness, disgust, contempt, anger, fear, and surprise.	free availability with some restrictions
Kairos (Belyeu, 2018)	video (facial)	facial landmarks estimation, head orientation estimation, facial action unit recognition, and eye-gaze estimation	joy, sadness, disgust, anger, fear, and surprise.	free availability for personal use
openVokaturi (Vokaturi, 2018)	audio	spectral, prosodic, voice quality (partially specified)	happiness, sadness, anger, fear and neutrality	free availability with some restrictions

4.3 Conclusions and Discussion

Wearable devices such as smartphones and smartwatches have been used relatively much in healthcare research to collect clinical health data, monitor patient's vital signs and deliver comprehensive healthcare information to practitioners, researchers and patients, by enhancing the ability to diagnose and track diseases (Silva, et al., 2015). Specifically, the sensing modalities of a wearable device can lead to human behaviour understanding by detecting short-term and long-term behaviours.

Human behaviour understanding can be divided into four main categories, including physical activity, cognitive, emotional and social behaviour. Short-term behaviour can be defined as physical, cognitive, emotional or social behaviour that last for a certain period of time (e.g. hours, days). On the other hand, long-term behaviour can be defined as the concatenation of short-term behaviours over a prolonged period of time (e.g. weeks, months). Consequently, long-term behaviours depend on the purpose of the application for behaviour monitoring, and can be related to clinical conditions or disorders. For instance, depression, which is defined as a mental disorder due to low mood, can be only detected after a period of at least two weeks (Association, 2013), where a person is continuously sad (short-term emotional behaviours over a longer period).

In order to detect human behaviour, data from different sensors have to be processed and analysed. Wearables' motion sensors, such as accelerometer and gyroscope, but also other sensors, such as GPS, Wi-Fi and Bluetooth (signal strength), have been used to detect the user's activity and movement (for example sitting, walking, running, eating or performing more complicated hand gestures) (Gravenhorst, et al., 2015). Data related to screen touch events and user's response time can be used to track short term cognitive states, such as attention and alertness (Torous, Kiang, Lorme, & Onnela, 2016). Phone calls and text messages can be used to monitor the user's social life (Frost, et al., 2013), while audio and microphone signals (or physiological signals through smartwatches), combined with the user's physical activity, can be used to detect user's mood (boredom, happiness, anxiety, etc.) (Kamdar & Wu, 2016) (Muaremi, et al., 2014). In addition, the accurate prediction of short-term behaviours can lead to the monitoring and prediction of long-term behaviours.

Despite the fact that human behaviour understanding cannot be easily addressed, it is still a challenging research area with a great impact on healthcare. Based on the existing studies in human behaviour understanding through sensing technologies, it is clear that the contribution of combining the aforementioned sensing modalities has not been examined thoroughly. Thus, the main aim of this WP is to combine the aforementioned sensing modalities that can reveal relevant determinants of health. For instance, short-term emotional states, such as sadness, that remain the same over a continuous period of time, can be used to detect a long-term mental state, such as depression (see also Figure 2). In the following table, an abstract explanation of the different sensing modalities is presented.

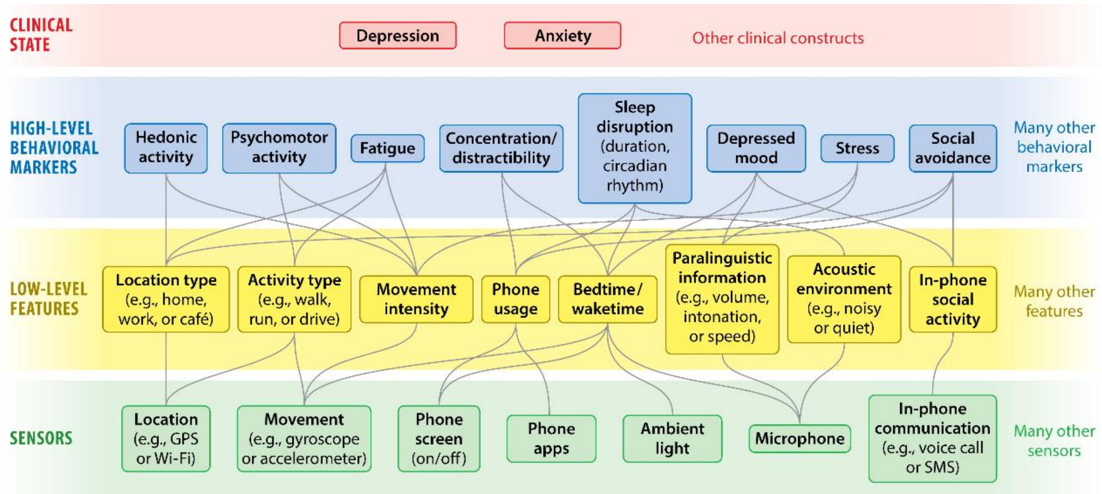

Figure 2: illustration of a layered hierarchical sense-making framework (Mohr, Zhang, & Schueller, 2017)

Table 11: Summary of sensing modalities using smartphones and smartwatches.

Wearable Device	Sensors	Features	Sensing Modality	Short-term Behaviours	Long-term Behaviours (*needs further investigation)
smartphone & smartwatch	motion (e.g. accelerometer and/or gyroscope)	time-domain (e.g. mean, variance, correlation) frequency-domain (e.g. FFT components)	physical activity	counting steps and/or simple physical activities (e.g. walking, sitting, standing) and/or complicated activities (e.g. shopping, eating, working) and/or gait analysis and/or fall detection and/or sleep duration and/or body balance and/or hand movements	monitoring health and well-being and/or chronic diseases* (e.g. cardiovascular, stroke, rheumatoid arthritis, Parkinson disease, Diabetes)
smartphone & smartwatch	outdoor location (e.g. GPS)	amount of time spent outdoors, distances travelled, frequency of visited places, regularity of daily habits, etc.	physical & social activity	location detection and movement analysis and/or social interaction/isolation	emotional – mental state, such as depression
	indoor location (e.g. Bluetooth, and/or Wi-Fi signals)	the amount and signal strength of visible Wi-Fi or Bluetooth stations			
smartphone & smartwatch	device usage patterns	speed of reaction time	cognitive activity	alertness, attendance, fatigue assessment	schizophrenia* and depression
smartphone	SMS, phone calls, audio and microphone	content, number of ingoing/outgoings calls and texts, etc.	emotional & social activity	emotional states and mood and/or social interaction/isolation	emotional – mental state, such as depression
smartwatch	physiological signals (such as heart rate, GSR, skin temperature)	time-domain (e.g. mean, variance) frequency-domain (e.g. FFT components)	cognitive & emotional activity	emotional states and/or stress	anxiety, sleep apnoea*

5 Holistic Behaviour Analysis Framework

As was described in Section 2, the second objective of this deliverable is to present an initial design for the Behaviour Analysis Framework (HBAF). In the following subsections, we present the initial set of functional and non-functional requirements elicited from a technical point of view. These requirements are subject to modification after evaluating the requirements collected from users, customers and relevant stakeholders (see D2.2). Moreover, we specify initial use cases for the initial design of the HBAF.

5.1 Requirements Analysis

Based on Section 4 and the state-of-the-art sensing technologies for human behaviour understanding, it was found that a holistic approach is needed for measuring the different components of human behaviour. This holistic approach involves multimodal sensor data from multiple on-body & off-body devices, with different sensor types and different data generation rates. Thus, the main aim of this subsection is to determine the system requirements for such a holistic approach, by describing the functional and non-functional requirements of the HBAF.

5.1.1 Functional Requirements

The aim of this subsection is to elaborate the functional requirements (FR) found in HBAF. Overall, functional requirements describe a functionality or a particular behaviour of the system under certain conditions (e.g., system functions, inputs and outputs, exceptions, etc.). Table 12 outlines the initial set of functional requirements identified for the HBAF.

Table 12: Summary of the functional requirements in HBAF.

Requirement	Description
FR-01	The platform shall authorise devices to send data
FR-02	The platform shall read raw sensory data from authorised devices
FR-03	The platform shall store raw sensory data from authorised devices
FR-04	The platform shall obtain raw sensory data from each device
FR-05	The platform shall provide a UDI for each device
FR-06	The platform shall provide a UUI for each user
FR-07	The platform shall link each UDI with the related UUI
FR-08	The platform shall compute features based on raw sensory data
FR-09	The platform shall provide the appropriate data for each feature extraction model
FR-10	The platform shall provide the appropriate features for creating the classification model
FR-11	The platform shall facilitate the generation of datasets for training the classification model
FR-12	The platform shall update the classification model
FR-13	The platform shall create logs of behaviours
FR-14	The platform shall update logs of behaviours
FR-15	The platform shall allow concurrent access
FR-16	The platform shall identify user's short-term behaviours
FR-17	The platform shall provide short-term behaviours for the generation of behaviour logs
FR-18	The platform shall provide the appropriate short-term behaviours for recognising long-term behaviours
FR-19	The platform shall identify user's long-term behaviours

FR-20	The platform shall provide to the authorised entities permissions to read, write, delete and update behavioural logs
FR-21	The platform shall provide to the authorised entities permissions to read, write, delete and update raw sensory data
FR-22	The platform shall merge behavioural data coming from external sources

5.1.2 Non-Functional Requirements

The aim of this subsection is to elaborate the non-functional requirements (NFR) found in HBAF. Non-functional requirements specify how the system should perform a specific function, taking into account constrains on the services or functions offered by the system (e.g., performance, security, availability, etc.). Table 13 outlines the initial set of non-functional requirements identified for the HBAF.

Table 13: Summary of the non-functional requirements in HBAF.

Requirement	Description
NFR-01	The platform shall read the raw sensory data of the user from his/her personal device in real-time with a delay of no more than 3 seconds
NFR-02	The platform shall maintain the consistency, integrity, and reliability of raw sensory data in non-volatile storage
NFR-03	Overall the accuracy of short-term behaviour detection shall be greater than or equal to 80%
NFR-04	Overall the accuracy of long-term behaviour detection shall be greater than or equal to 70%
NFR-05	Overall the percentage of missing data that is allowed shall be less than 20%
NFR-06	The platform shall ensure consistency of distributed copies of behavioural data.
NFR-07	The platform response time to a data request shall be below 30 seconds

5.2 Use Case Specifications

Once the requirements analysis is performed and the functional and non-functional requirements are introduced, it is important to precisely describe each one of the essential requirements. The aim of this subsection is to present a textual representation of the HBAF requirements through use cases (UC), based on a sequence of events that cover the HBAF system.

5.2.1 Use case index

Nine use cases are developed and presented in Table 14.

Table 14: Summary of the HBAF use cases.

Use Case ID#	Name
UC-01	Authorise user's device for gaining access to the platform
UC-02	Receive and store raw sensory data from the authorised device
UC-03	Associate user identifier to each connected device
UC-04	Extract features from raw sensory data
UC-05	Select relevant features for short/long-term behaviour detection
UC-06	Train the behaviour detection model
UC-07	Update the behaviour detection model
UC-08	Detect short/long-term behaviours
UC-09	Detect behaviour changes

5.2.2 Use cases

The aforementioned use cases and their specifications are elaborated in the following tables 15-23.

5.2.2.1 UC-01: Authorise user's device for gaining access to the platform

Table 15: Use Case 01: Authorise user's device for gaining access to the platform.

Use Case ID:	**UC-01**		
Use Case Name:	Authorise user's device for gaining access to the platform		
FR ID:	FR-01, FR-15		
Created By:	Kostas Konsolakis	Last Updated By:	
Date Created:	12 February 2018	Last Revision Date:	
Actors:	User's Device, HBAF		
Description:	The necessary credentials are required in order to establish a connection between the data source and the HBAF platform		
Trigger:	Request connection from a device to the HBAF platform		
Pre-conditions:	-		
Post-conditions:	Raw data are sent from the data source		
Normal Flow:	1. Request connection 2. Authorise user 3. Authorise device 4. Gain access		
Alternative Flows:	2a. If the user has been already authorised then 1. Request connection 2. Authorise device 3. Gain access		
Exceptions:	-		
Includes:	NA		
Frequency of Use:	NA		
NFR ID:	NFR-01		
Assumptions:	1. The user will be authorised to connect with one or multiple devices		
Notes and Issues:	NA		

5.2.2.2 UC-02: Receive and store raw sensory data from the authorised device

Table 16: Use Case 02: Receive and store raw sensory data from the authorised device.

Use Case ID:	**UC-02**		
Use Case Name:	Receive and store raw sensory data from the authorised device		
FR ID:	FR-02, FR-03, FR-15		
Created By:	Kostas Konsolakis	Last Updated By:	Kostas Konsolakis
Date Created:	30 January 2018	Last Revision Date:	13 February 2018
Actors:	HBAF		
Description:	Raw sensory data are sent from an authorised user's device to the platform		
Trigger:	Send raw sensory data from authorised devices to the HBAF platform		
Pre-conditions:	User has been authorised to send data to HBAF platform		
Post-conditions:	1. Raw sensory data are received by the HBAF 2. Raw sensory data are persisted in a non-volatile storage by the HBAF		
Normal Flow:	1. HBAF receives the raw sensory data from the device 2. HBAF authenticates the raw sensory data 3. HBAF buffers the received sensory data 4. The received raw sensory data is persisted in a non-volatile storage		
Alternative Flows:	NA		
Exceptions:	In step 1 of the normal flow, if the user is detected to be unauthorised then the connection will be terminated and not access to data source will be gained.		
Includes:	NA		
Frequency of Use:	Very frequent: determined by the rate of sensory data reception from HBAF		
NFR ID:	NFR-01		
Assumptions:	1. There is an established communication between actors and HBAF 2. The communication channel between the actors and the HBAF is secure		
Notes and Issues:	NA		

5.2.2.3 UC-03: Associate user identifier to each connected device

Table 17: Use Case 03: Associate user identifier to each connected device.

Use Case ID:	**UC-03**		
Use Case Name:	Associate user identifier to each connected device		
FR ID:	FR-04, FR-05, FR-06, FR-07, FR-15		
Created By:	Kostas Konsolakis	Last Updated By:	Kostas Konsolakis
Date Created:	30 January 2018	Last Revision Date:	13 February 2018
Actors:	Users' Device, HBAF		
Description:	The platform is able to receive raw sensory data from simultaneously connected devices, and differentiate each user and his/her device based on a unique identifier.		
Trigger:	Receive raw sensory data		
Pre-conditions:	User has been authorised to register as client to HBAF platform		
Post-conditions:	Raw sensory data are processed to extract behavioural logs		
Normal Flow:	1. Read the UDI for each connected device 2. Provide a UUI for each connected user 3. Correlate the UUI with the relevant UDI 4. Store raw sensory data		
Alternative Flows:	NA		
Exceptions:	In step 1 of the normal flow, if the user is detected to be un-authorised then the dialogue will be terminated and not access to data source will be gained.		
Includes:	NA		
Frequency of Use:	Very frequent: determined by the rate of sensory data reception from HBAF		
NFR ID:	NFR-01, NFR-02		
Assumptions:	1. There is an established communication between actors and HBAF 2. The communication channel between the actors and the HBAF is secure 3. A user can connect with the same UUI using also multiple devices and UDI 4. Multiple users can connect to the platform simultaneously		
Notes and Issues:	NA		

5.2.2.4 UC-04: Extract features from raw sensory data

Table 18: Use Case 04: Extract features from raw sensory data.

Use Case ID:	**UC-04**		
Use Case Name:	Extract features from raw sensory data		
FR ID:	FR-08, FR-09		
Created By:	Kostas Konsolakis	Last Updated By:	Oresti Banos
Date Created:	30 January 2018	Last Revision Date:	7 February 2018
Actors:	HBAF		
Description:	The platform computes features from raw data in order to classify and detect behaviours		
Trigger:	Receive raw sensory data		
Pre-conditions:	Raw data are successfully stored		
Post-conditions:	Select relevant features		
Normal Flow:	1. Read raw sensory data 2. Extract features 3. Store features		
Alternative Flows:	NA		
Exceptions:	If the dataset is incomplete, repeat step 1 of the normal flow		
Includes:	NA		
Frequency of Use:	NA		
NFR ID:	NFR-02, NFR-03, NFR-04, NFR-05		
Assumptions:	1. Raw sensory data are stored		
Notes and Issues:	NA		

5.2.2.5 UC-05: Select relevant features for short/long-term behaviour detection

Table 19: Use Case 05: Select relevant features for short/long-term behaviour detection.

Use Case ID:	**UC-05**		
Use Case Name:	Select relevant features for short/long-term behaviour detection		
FR ID:	FR-08, FR-09, FR-10		
Created By:	Kostas Konsolakis	Last Updated By:	Oresti Banos
Date Created:	30 January 2018	Last Revision Date:	7 February 2018
Actors:	HBAF		
Description:	The platform selects the most relevant features in order to classify accurately and detect short/long-term behaviours		
Trigger:	Receive features		
Pre-conditions:	Features are extracted from raw data		
Post-conditions:	The features are made available to all classification models for training and prediction		
Normal Flow:	1. Read features 2. Select the relevant ones		
Alternative Flows:	NA		
Exceptions:	If the features are missing or corrupted, repeat step 1 of the normal flow		
Includes:	NA		
Frequency of Use:	NA		
NFR ID:	NFR-02, NFR-03, NFR-04, NFR-05		
Assumptions:	1. Features are stored		
Notes and Issues:	NA		

5.2.2.6 UC-06: Train the behaviour detection model

Table 20: Use Case 06: Train the behaviour detection model.

Use Case ID:	**UC-06**		
Use Case Name:	Train the behaviour detection model		
FR ID:	FR-10, FR-11		
Created By:	Kostas Konsolakis	Last Updated By:	
Date Created:	30 January 2018	Last Revision Date:	
Actors:	Engineer		
Description:	The behaviour detection model is trained in order to detect short-term /long term behaviour		
Trigger:	The engineer will initiate the training of the model		
Pre-conditions:	Relevant features are extracted		
Post-conditions:	The training model will be ready for detecting behaviours		
Normal Flow:	1. Load most relevant features 2. Train the classification model 3. Store the classification model		
Alternative Flows:	NA		
Exceptions:	If the dataset is incomplete, repeat step 1 of the normal flow		
Includes:	NA		
Frequency of Use:	NA		
NFR ID:	NFR-03, NFR-04		
Assumptions:	1. There will be annotated data		
Notes and Issues:	NA		

5.2.2.7 UC-07: Update the behaviour detection model

Table 21: Use Case 07: Update the behaviour detection model.

Use Case ID:	**UC-07**		
Use Case Name:	Update the behaviour detection model		
FR ID:	FR-10, FR-12		
Created By:	Kostas Konsolakis	Last Updated By:	
Date Created:	30 January 2018	Last Revision Date:	
Actors:	Engineer		
Description:	The behaviour detection model is updated in order to detect short-term /long term behaviour		
Trigger:	The engineer will update the training of the model		
Pre-conditions:	New features data are extracted and there is already a trained model		
Post-conditions:	The training model will be ready for detecting behaviours		
Normal Flow:	1. Load new relevant features 2. Retrain the classification model 3. Replace the existing classification model with the updated one		
Alternative Flows:	NA		
Exceptions:	If the dataset is incomplete, repeat step 1 of the normal flow		
Includes:	NA		
Frequency of Use:	NA		
NFR ID:	NFR-03, NFR-04		
Assumptions:	1. There will be annotated data		
Notes and Issues:	NA		

5.2.2.8 UC-08: Detect short/long-term behaviours

Table 22: Use Case 08: Detect short/long-term behaviours.

Use Case ID:	**UC-08**		
Use Case Name:	Detect short/long-term behaviours		
FR ID:	FR-13, FR-14, FR-15, FR-16, FR-17, FR-18, FR-19		
Created By:	Kostas Konsolakis	Last Updated By:	
Date Created:	30 January 2018	Last Revision Date:	
Actors:	HBAF		
Description:	The platform detects physical/cognitive/emotional/social behaviours and creates or updates logs of short and long-term behaviours		
Trigger:	Receive features for classification		
Pre-conditions:	Relevant features are extracted and there is a trained model		
Post-conditions:	Create logs of behaviours		
Normal Flow:	1. Load most relevant features 2. Classify features into physical/cognitive/emotional/social behaviours 3. Create/update logs of short/long-term behaviours		
Alternative Flows:	NA		
Exceptions:	If the dataset is incomplete, repeat step 1 of the normal flow		
Includes:	NA		
Frequency of Use:	NA		
NFR ID:	NFR-02, NFR-03, NFR-04, NFR-05, NFR-06, NFR-07		
Assumptions:	1. Relevant features are selected		
Notes and Issues:	NA		

5.2.2.9 UC-09: Detect behaviour changes

Table 23: Use Case 09: Detect behaviour changes.

Use Case ID:	**UC-09**		
Use Case Name:	Detect behaviour changes		
FR ID:	FR-16, FR-19, FR-20, FR-21, FR-22		
Created By:	Kostas Konsolakis	Last Updated By:	
Date Created:	30 January 2018	Last Revision Date:	
Actors:	HBAF, Council of Coaches System		
Description:	The HBAF detects behaviour changes based on a time series and notifies the Council of Coaches System		
Trigger:	The process is initiated periodically		
Pre-conditions:	Short/long-term behaviours		
Post-conditions:	The Council of Coaches system will be notified with the relevant behaviour change		
Normal Flow:	1. Select a time series of behaviour data 2. Detect changes in this time series 3. Notify the Council of Coaches system		
Alternative Flows:	NA		
Exceptions:	If the dataset is incomplete, repeat step 1 of the normal flow		
Includes:	NA		
Frequency of Use:	NA		
NFR ID:	NFR-02, NFR-06, NFR-07		
Assumptions:	1. There is a time series of behaviour data		
Notes and Issues:	NA		

5.3 Initial Holistic Behaviour Analysis Framework Design

A high level initial design of the HBAF architecture is presented in the following figure (see Figure 3), clearly mentioning the main system components, with the relevant inputs/outputs.

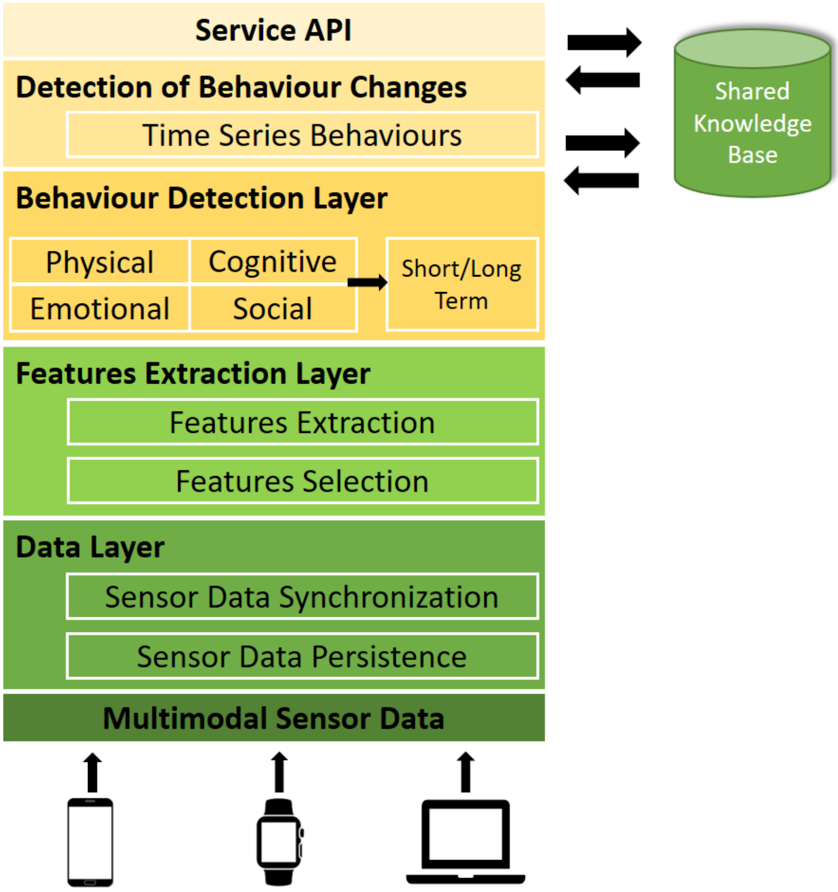

Figure 3: Initial design of HBAF architecture.

5.4 Open Issues

After developing the HBAF system's requirements and specifications, several points are considered controversial and need further clarification between the involved Work Packages. Thus, the following points of attention are formulated as questions and need further examination from the relevant Work Packages.

- **[WP3, 5, 6, 7]** What should be the final definition for short/long term behaviour? Is there any recommended taxonomy that we should consider?
- **[WP3]** How will the Shared Knowledge Base interact with the HBAF?
- **[WP3]** Are there any specific behaviours coming from the coaching strategies of the Council of Coaches system?
- **[WP5]** Based on the argumentation framework, what will be the real-time behaviour related to steering dialogues and conversations (between the Council of Coaches and the subject)?
- **[WP6]** How will the Council of Coaches interact to user responses in a fluent way?

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