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Automatic Performance Status Evaluation and Physical Activity Recognition in Cancer Patients for Medical Diagnosis Assistance

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Resumen. La evaluación de la recuperación de pacientes con cáncer está caracterizada por un alto grado de subjetividad en los diagnósticos del personal médico. Se han implementado con éxito diferentes sistemas para la evaluación de la actividad física, sin embargo, aún existe un amplio margen de evolución dentro de la medida de la capacidad funcional con las escalas ECOG y de Karnofsky. En este proyecto se ha diseñado un sistema automático para la biomonitorización de pacientes basado en tecnología Android con smartphones y wearables. Con esto se provee a los oncólogos de datos objetivos para sus diagnósticos junto con nuevos algoritmos para la evaluación de la actividad física y la capacidad funcional, estos últimos aplicados a ECOG y la escala de Karnofsky sin precedente alguno. Además, se han sentado las bases y el diseño de una futura implementación de gamificación para favorecer la motivación del paciente en su recuperación.

Palabras calve. mHealth, eHealth, actividad física, capacidad funcional, recuperación en el cáncer, Android, wearables, smartwatch, Internet de las Cosas, gamificación, ludificación.

Abstract. The evaluation of cancer patients' recovery is still under a big grade of subjectivity from the physicians' diagnoses. Different systems have been successfully implemented for general physical activity evaluation, nonetheless there is still a big leap of improvement into Performance Status (PS) evaluation with ECOG and Karnofsky's Performance Status (KPS) scores. In this project an automatic system for patients' biomonitoring based on Android technology with smartphones and wearables has been designed. As a result, objective data is provided for the oncologists' diagnoses along with new algorithms for physical activity and PS assessment, having the latter applied to ECOG and KPS no precedent known. Furthermore, the basics for prospective implementation of gamification has been designed for boosting patients' motivation in their recovery.

Keywords. mHealth, eHealth, physical activity, performance status, cancer recovery, Android, wearables, smartwatch, Internet of Things, gamification.

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AUTORIZO: al depósito de dicho Trabajo en la Secretaría del Departamento de Arquitectura y Tecnología de Computadores, y a su visualización bajo firma de documento de confidencialidad

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Preface

When I decided to start this project as my End-of-Degree Thesis, I was not aware of the actual amount of work, problems and time investment I was going to deal with. I have had to tackle with several disciplines from very different areas of study such as cancer patients' assessment, physical activity evaluation, gamification, computer programming, data processing and database management. This has lead me to me to learn many new and specific concepts from all of those subjects that will be introduced along the document presented.

However, I would like to highlight the love and effort put into this work. Gathering all the presented elements into one solid functional system is just the beginning of a new way to assess cancer patient's diagnosis. The fascinating thing is that this work does not end here, it opens several new areas of study and application on which I intend to keep working on in the near future.

I hope you reader like this work as much as I did making it.

Salvador Moreno Gutiérrez.

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Chapter 1

Introduction

1.1 Motivation

According to the World Health Organization, cancer is the plague of the XXI century. It has become the major cause of mortality and morbidity, with 14 million new cases and 8 million deaths related to cancer in 2012, affecting all the regions over the world. Moreover, these figures are expected to keep growing during the next years [1, 2].

One of the worst parts of facing cancer is the widely known aggressive impact of the treatment based on chemotherapy and radiotherapy [3]. The side effects stuck patients in a loop of asthenia and physical activity weakness from which is hard to come out from [4]. Many studies have valued positively the effects of exercise in patients, improving survival probability [5, 6, 7, 8]. Furthermore, some apps and systems including gamification techniques have reported successful results in increasing users' physical activity in diverse areas like obese children [9], chemotherapy-induced peripheral neuropathy affected cancer patients [10], general fitness [11], and some early proposals specially designed for adult and children cancer patients [12, 13, 14].

Oncologists use the Performance Status (PS) measurements like Karnofsky's PS (KPS) [3] and Eastern Cooperative Oncology Group PS (ECOG) [15] to evaluate the overall patient's status. It serves, short-term, as a critical measure to determine if a patient can handle a new session of treatment and, long-term, as a key pointer of the survival probabilities of the patient [16, 17, 18, 19]. Despite the relevance of the PS measure, there has always been some controversy when applied since there is always quite a big subjective component from every oncologist in its evaluation. Different studies have determined a Kendal correlation coefficient of 0.75 of reliability when several oncologists evaluate the same patients, that is, 3 out of 4 oncologists catalogue in the same PS to the patient whilst the left one does not [20, 21]. There is an obvious need for objectivity with measures.

There are also other tools like the International Physical Activity Questionnaire (IPAQ) that focus exclusively in the physical activity performed [22]. However, it is still applied in hospitals in an outdated self-reported filling up a questionnaire. The patient needs to remember all the activity done in a whole week and, besides, evaluate himself the intensity of the exercise done by filling up a blank questionnaire.

On the other hand, we live nowadays in the era of the data and the Internet, where almost everybody in the world is connected via any sort of PC, smartphone or simply any other kind of mobile device, leading us to the brand new trend of the Internet of Things (IoT). Smartwatches and activity trackers are some of the technologies that can be found on the popular market of fitness and wearables that also deal with the concept of IoT applied to Mobile Health (mHealth) [23]. mHealth is the integration of medicine and public health practices into portable devices such as mobile phones, tablet computers or wearables. mHealth emerges from the electronic health (eHealth) sector, always within the context of Information and Communication Technology (ICT), but primarily focusing in the use of the cutting edge technologies that enable data monitoring through a Body Sensor Network (BSN) or a Personal Area Network (PAN) [24].

New kind of sensors are being implemented into this mobile devices such as accelerometers, barometers or even photoplethysmograms. The evaluations found in the literature support long-term evaluation of patients with photoplethysmography (PPG) for heart rate (HR) monitoring despite its need for improvement [25, 26]. Accelerometers have been used in the field for many kinds of physical activity evaluation, like steps counting and [27].

1.2 Objectives

The purpose of this project is double: to help oncologists in their diagnosis of PS with an automatic estimation of ECOG or KPS based in objective data, and to set the basic implementation for a gamified app to improve cancer patient's recovery. The data will be provided by a biomonitoring system based on portable and wearable devices.

After an extent art review and some interviews with specialists from the hospital *Virgen de las Nieves (Granada)*, the oncologist Victor Amezcua, the psychologyst Pilar Gutiérrez and the specialist in radiopharmacy Ángel Ramírez, the following needs are concluded:

1. Design the gamified system around a smartphone plus wearable system.
2. Implement patient's tracking with a smartphone-wearable system to obtain objective data.
3. Develop algorithms for automatic IPAQ inferring week by week.
4. Develop algorithms for automatic ECOG and KPS inferring week by week.
5. Focus on tendencies rather than absolute measurements. Allow data displaying along for evolution tracking.

1.3 Document's Structure

The document is divided according to the following scheme:

- Chapter 1: Introduction. Motivation and basic support of the project.
- Chapter 2: State of the Art. A review of the relevant part of the literature it has been relevant developing this project.
- Chapter 3: System Design. A systematic review of the Hardware and Software employed according to the specific requirements and needs deployed.

- Chapter 4: System Implementations and Results. A description of the data gathering app and the algorithms used to infer IPAQ, ECOG and KPS.
- Chapter 5: Conclusions. A summary of the results obtained and the future work proposed.
- Chapter 6: Appendix.

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Chapter 2

State of the Art

2.1 Cancer Patients' Recovery

Cancer patients face many challenges during their process of recovery, both in a physical [1, 2] and a mental way [3, 4]. This recovery implies, most of the times, an aggressive treatment with chemotherapy and radiotherapy that leads the patient to a state of asthenia and general physical weakness with several side effects. Performance Status (PS) scales emerge as the solution for cancer patients assessment, pointing out whether an individual is able to receive a session of chemotherapy or radiotherapy, or not. These PS scales are also an indicator of the survival probability, specially when analyzed along the whole period of treatment [5, 6, 7, 8].

2.1.1 Performance Status Evaluation

There are several more Performance Status Scales such as the KPS and ECOG already mentioned. Some of them are the Lansky score [9] for children, the Palliative Performance Scale [10], which focus on palliative care to propose a solution for those patients in the last stages of irreversible cancer, the Edmonton Functional Assessment Tool [11] for terminal patients, or the Katz Index [12] and the Barthel Index [13], both for geriatric patients.

In this project the approach for PS estimation is tackled from the perspective of the ECOG and KPS scores. Both scales were the first proposals to PS evaluation (each one with its own range) in cancer patients and they are still widely used across the world. Besides, since the rest of indexes are adaptations and modifications of KPS and ECOG for specific solutions, it seems reasonable to start the approach of automatic PS estimation with KPS and ECOG.

It is important to highlight that **no paper related to automatic PS evaluation was found** throughout the extent review done within the search engines of *Scopus* and *Web Of Science*.

Karnofsky's Performance Status

Karnofsky's Performance Status (KPS) is a measure developed by Karnofsky and Burchenal in 1949 to evaluate cancer patients' condition and planning their treatment [1]. The KPS classification goes from 0 (worst case, death) to 100 (best case, asymptomatic) and it is depicted in Table 2.1.

The most important gap in the KPS is the one between 50 and 60. It matches the gap between 2 and 3 ECOG (see ECOG/WHO/Zubrod Performance Status, page 15) which determines if a patient is able to receive a session of chemotherapy for treatment [6]. Scoring 60 KPS implies "ocassional assistance but able to care for most of personal needs", that is, a symptomatic patient but still strong enough to live mostly by his/her own. On the other hand, scoring below that level comes always with "considerable assistance and frequent medical care", in a higher (10 KPS) or lower (50 KPS) degree depending on the impact of the symptoms. Several studies have validated its reliability for PS and survival prediction [5, 14, 8]. Besides, there is no denial of the big impact of the scale in its field, even serving as the basis for other measures like the Palliative Performance Scale.

However, some studies have pointed out critics that may have an impact on this reliability [15, 16, 17]. Those critics can be summed up in three points:

1. The gap between the different levels in the scale does not match in the same proportion to the functional disability reflected. This means that there is not the same difference in functional disability in the gap between levels 70 and 60 than the one between 40 and 30.

2. The higher the level in the scale, the lower the reliability. This project also looks forward to improve reliability in that major categories which doctors fail to evaluate due to the lack of proper data and monitoring.

3. Results may vary depending on the observer and its medical role (doctor, nurse), and the place of evaluation (place of residence, consulting room, hospital).

It has also been reported a noticeable difference between the PS evaluated by the physician and the patient's self-evaluated PS in which medical personnel tend to assign patients better PS than they may feel [8]. However, it can be highlighted that the KPS scores a good Kendall's correlation coefficient 0.65 when comparing doctor's evaluation and patient's own evaluation with this score [18].

ECOG/WHO/Zubrod Performance Status

Score developed by the *Eastern Cooperative Oncology Group* (ECOG) with the same PS evaluation purposes as KPS [2]. The ECOG scale goes from 5 (worst case, death) to 0 (best case, asymptomatic) and it is depicted in Table 2.2. The most important gap in the ECOG scale is the one between 3 and 2. It determines whether the patient is capable of receiving a session of chemotherapy (ECOG 2 or lower) or not (ECOG 3 or higher). Scoring 2 implies being 'Symptomatic, less than 50% of waking hours in bed, and capable of self care but unable to carry out any work activities', whilst 3 is for 'Symptomatic, more than 50% of waking hours in bed, and limited self-care'.

The reliability and validity of this scale has been studied by different authors obtaining very good results for PS as an evaluation and survival probability estimation tool [19, 18, 8, 7].

It can be highlighted that the ECOG scores a good Kendall's correlation coefficient 0.59 when comparing doctor's evaluation and patient's own evaluation with this score [18].

Karnofsky's Performance Satus score (Karnofsky and Burchenal, 1949)	
100	Normal; no complaints; no evidence of disease.
90	Able to carry on normal activity; minor signs or symptoms of disease.
80	Normal activity with effort; some signs or symptoms of disease.
70	Cares for self; unable to carry on normal activity or to do active work.
60	Requires occasional assistance, but is able to care for most of their personal needs.
50	Requires considerable assistance and frequent medical care.
40	Disabled; requires special care and assistance.
30	Severely disabled; hospital admission is indicated although death not imminent.
20	Very sick; hospital admission necessary; active supportive treatment necessary.
10	Moribund; fatal processes progressing rapidly.
0	Dead

Table 2.1: Karnofsky's Performance Status Score

Moreover, when comparing ECOG and KPS Spearman's correlation coefficient 0.85 ($p < 0.0001$) was scored in [8] and 0.87 ($p < 0.0001$) in [6]. The latter work proposes a three-grades conversion table where ECOG 0 and 1 matches 100, 90 and 80 KPS; ECOG 2 matches 70 and 60 KPS; ECOG 3 and 4 matches KPS < 60.

2.1.2 Physical Activity

The relevance of Physical Activity (PA) in health is not only for those who do not suffer any condition, some studies have outlined the benefits of regular exercise in cancer patients along treatment and after recovery [20, 21, 22, 23].

PA may have a direct and beneficial impact on Heart Rate Variability (HRV) which is directly related to the activation of the sympathetic and parasympathetic nervous activity, hence the regulation of the autonomous nervous system (ANS) [24, 25]. The ANS controls, among other

ECOG/WHO/Zubrod Performance Status score (Zubrod et al., 1960)	
0	Asymptomatic (Fully active, able to carry on all predisease activities without restriction)
1	Symptomatic but completely ambulatory (Restricted in physically strenuous activity but ambulatory and able to carry out work of a light or sedentary nature. For example, light housework, office work)
2	Symptomatic, <50% in bed during the day (Ambulatory and capable of all self care but unable to carry out any work activities. Up and about more than 50% of waking hours)
3	Symptomatic, >50% in bed, but not bedbound (Capable of only limited self-care, confined to bed or chair 50% or more of waking hours)
4	Bedbound (Completely disabled. Cannot carry on any self-care. Totally confined to bed or chair)
5	Dead

Table 2.2: ECOG/WHO/Zubrod Performance Status score

things, acute physiological responses to psychophysical stress, but its adequate performance can be undermined by any chronic condition like cancer [26]. Thus, a better performance of the ANS comes with a general improvement of body self-recovery.

Metabolic Equivalent of Task (MET)

The most direct way to evaluate a PA is by comparing the calorie expenditure of each activity for every patient. However, this value depends deeply on different personal conditions such as weight, height, age and gender. Thus, it is preferably used a normalized measure that takes into account all those variables, the Metabolic Equivalent of Task (MET) [27].

MET was defined in the *Compendium of Physical Activities* for use in epidemiologic studies to standardize the assignment of MET intensities in PA questionnaires. It is a physiological measure that express the energy cost of physical activities and is defined as the ratio of metabolic rate during a specific PA. It is set by convention:

$$1\ MET = 3,5\frac{ml\ O_2}{kg \cdot min} = 1\frac{kcal}{kg \cdot h} = 4.184\frac{kJ}{kg \cdot h}$$

In the beginning, 1 MET was considered as the Resting Metabolic Rate (RMR) obtained while quiet sitting. It should not be confused or misused as an approximation of the Basal Metabolic Rate (BMR), which is the minimum amount of energy expended under a physically and psychologically undisturbed state, in a thermally neutral environment (25 - 30 °C) and not actively digesting food [28]. BMR can be also referred as the minimal amount of energy necessary just to be alive.

International Physical Activity Questionnaire (IPAQ)

The IPAQ is a self-reported questionnaire for assessing PA and has been tested in 12 countries among adults aged 18 to 65 years [29]. It is normally obtained by making the subject fill up the questionnaire given with PA data (walking time, running time and so on) referred to the previous week. However, it seems reasonable to assume the difficulties that any person may have when remembering exactly how many minutes he/she walked, ran or lifted heavy loads. It is hard to count all the PA unless the subject has a very scheduled agenda; there are many situations in life that are usually taken out from the daily PA like walking from place to place. The detection of this kind of activity is tackled along the system proposed.

It has been validated in different studies with very different groups of people: elderly adults [30], Chinese people [31], Europe in general [32] or Swiss people [33]; resulting in a widely accepted validity [34]. All of these studies used raw accelerometer signals to measure steps count in a day and their cadence, classifying the intensity of the PA detected depending on the step levels registered.

There are two versions of the IPAQ, *short* and *long.* In this thesis the focus is presented over the *short* IPAQ since it is already being used in Spanish hospitals, more precisely, in all the Andalusian ones. There is a copy of the Spanish official version in the Appendix (see Short IPAQ, Spanish Version - Spain, Junta de Andalucia, page 88) and a copy of the original USA English version (see Short IPAQ, English Version - USA, page 84).

The IPAQ protocol evaluates the Energy Consumption (EC) using this formula:

$$EC = f \cdot minutesperweek \quad (MET)$$

where $f = \{3.3,\ 4,\ 8\}$ depending on the levels of PA defined, respectively, *light*, *moderate* and *vigorous*.

Physical Activity Intensity Estimation using Heart Rate

In order to evaluate the intensity of the PA, it is studied the effect of different levels of exercise in the patient's HR [35]. The different levels are the following:

- Low-intensity PA: for HR between 0% and 50% of maximum HR.
- Moderate-intensity PA: for HR between 50% and 70% of maximum HR.
- Vigorous-intensity PA: for HR between 70% and 100% of maximum HR.

There are different ways to calculate HR intensity, like the Zoladz and the Karvonen methods. In this work the latter is chosen since it is entirely a quantitative measure [36]. The Heart Rate Intensity (HRI) it is obtained by Karvonen formula as:

$$HRI = \frac{HR - HR_{rest}}{HR_{max} - HR_{rest}} \cdot 100\ [\%]$$

To calculate this HRI, it is necessary to define the minimum and the maximum HR.

The minimum is HR_{rest}, the **Resting Heart Rate (RHR)**. The RHR is the Heart Rate under minimun Physical Activity levels, is defined as the heart rate when a person is awake and within a neutrally temperate environment. The subject cannot have been altered by any recent exertion or stimulation like stress or surprise [37]. For this project, a RHR of 62 bpm has been considered after HR a study involving sleep traking through several days and taking the mean of HR when recently awaken.

There are several **Maximum Heart Rate (MHR)** estimation formulas, up to 53 different proposals from authors like Astrand, Fernandez, Jones et al., Karvonen et al., or Tanaka et al. [38]. Even though there is still controversy about the validity of this formulas and its application, in this work the Tanaka et al. (2001) version is to be used due to its good performance with young athletes [38, 39].

$$MHR = 208.75 - 0.73 \cdot age$$

It is important to note that for this work, the intention is to look for patients' tendencies above all, so a relative inaccuracy in HRI evaluation depending on the formula used, in the end, will not conduct the measures to flagrant error.

2.1.3 Physical Activity Intensity Estimation using daily Step Count

There is a common agreement regarding to the recommendation of 10 000 steps/day for most of the population [40, 41, 42]. Its validity has been demonstrated in the same papers, even including different ranges of steps for different sectors of society. However, it is necessary to define different levels to evaluate the effort done in exercise referring to steps done. Therefore, and looking into the work done in [42], different grades can be defined for most of the population:

- Sedentary: < 5000 *steps/day*.
- Low active: $5000 - 7499$ *steps/day*.
- Somewhat active: $7500 - 9999$ *steps/day*.
- Active: $10000 - 12499$ *steps/day*.
- Highly active: > 12500 *steps/day*.

For this work, this scale would be used for evaluating the effort of patients in the ECOG and KPS inferring.

2.2 mHealth within the IoT context.

mHealth is the integration of medicine and public health practices into portable devices such as mobile phones, tablet computers or wearables. It emerges from the electronic health (eHealth) sector, always within the context of Information and Communication Technology (ICT), but primarily focusing in the use of the cutting edge technologies that enable data monitoring through a Body Sensor Network (BSN) or a Personal Area Network (PAN). With this new kind of implementations, grown up in the cradle of the IoT, the picture of medicine goes beyond its traditional concept where the patient needs to personally attend to the hospital in order to be checked. Nowadays, this biomonitoring enables a higher relevance of prevention instead of treatment what is becoming the quintessence of modern medical care [43].

Looking at Figure 2.1 it can be seen how the IoT is already in the *Peak of Inflated Expectations*, according to the Gartner Hype Cycle Curve [44]. Thus, early procedures and implementations as the one proposed in this report characterize this moment for IoT.

There is still long way to go in the areas related to mHealth and the IoT in general, that is an ideal sector to take advantage of in both commercial and research levels.

A wide range of new wearable and different sensors are being used not only in research but also in the regular market. Photoplethysmography (PPG) is becoming the new standard for different measures such as heart rate monitoring and blood pressure. This technology is based on the optical obtention of a plethysmogram, that is, the volumetric changes of an organ. A pulse oximeter illuminates the skin and measures changes in light absorption to finally, monitor the perfusion of blood to the dermis and subcutaneous tissue of the skin [46]. Different wavelengths like infra-red, red and green have been implemented in the same device to improve performance [47]. Machine learning techniques are also being used to infer blood glucose levels from blood pressure [48]. Most of the devices in the wide spectrum of fitness trackers contain PPG embedded (Figure 2.2). It will be further analysed in section *Hardware* (page 30). Other technologies are being studied for wearable HR tracking such as using an in-ear piezoelectric sensor [49] and graphene-clad textile electrodes for direct attachment in clothes [50].

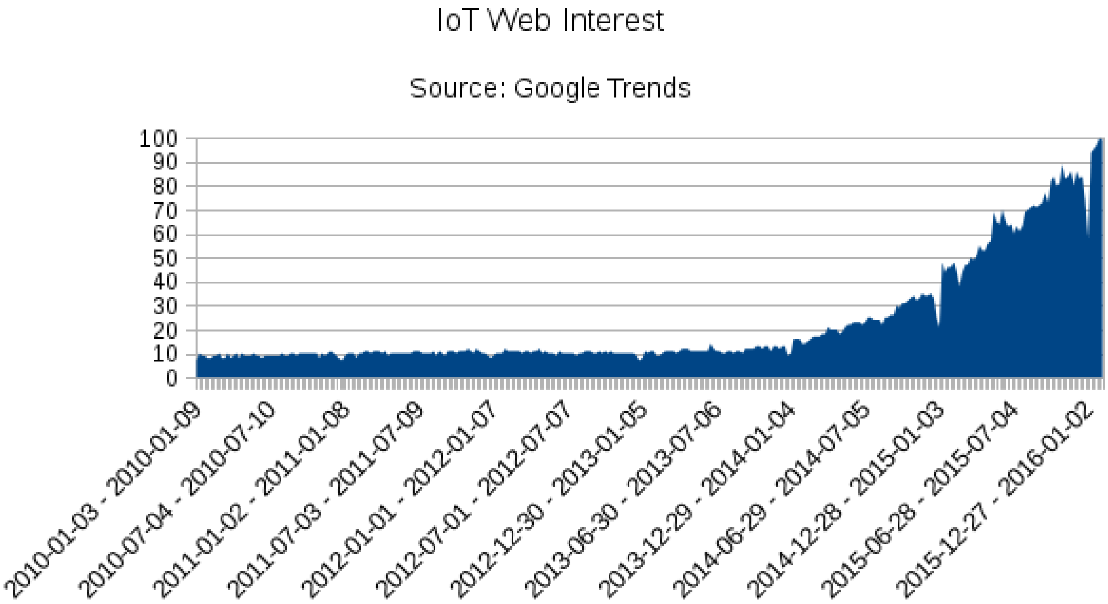

Figure 2.1: IoT Web Interest. Source Google Trends [45]

Many different projects have been found in the literature dealing with the issue of mHealth. For example, the use of pedometers for physical activity measurement through steps count [41]; the study of robust activity recognition based on multi-sensor fusion, considering non-ideal conditions [52]; or the use of a fully integrated wearable sensor array for sweat perspiration analysis [53]. Even full system approaches to general mHealth open frameworks have been developed [54]. The value of smartwatches and wristbands has also been studied in different papers referring to its validity for long-term HR monitoring [55] and for posture tracking [56], concluding both with good results.

All this sums up the good state of the mHealth and IoT field, where many different proposals are rising from the very same concept of taking modern medicine a step ahead with wearables and mobile devices.

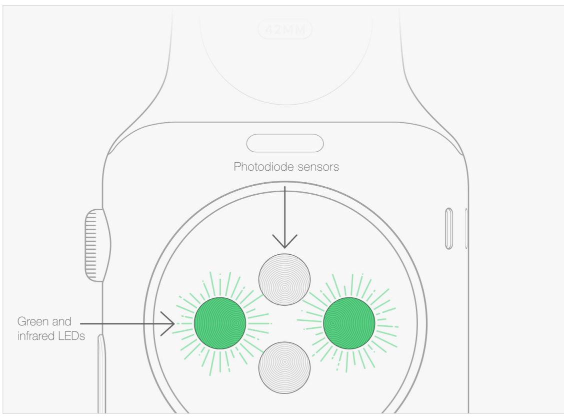

Figure 2.2: PPG embedded in a smartwatch. [51]

2.3 Gamification

Gamification is the inclusion of game-design elements and principles into non-game contexts [57, 58]. As it can be seen in Figure 2.3, the interest in Gamification may be already entering into the *Trough of Disillusionment* according to the Gartner Hype Cycle Curve [44]. That means that it is a good moment to start evaluating the different proposals along the literature to find out which are the key elements for successful implementation of gamification and how to introduce them properly into this work.

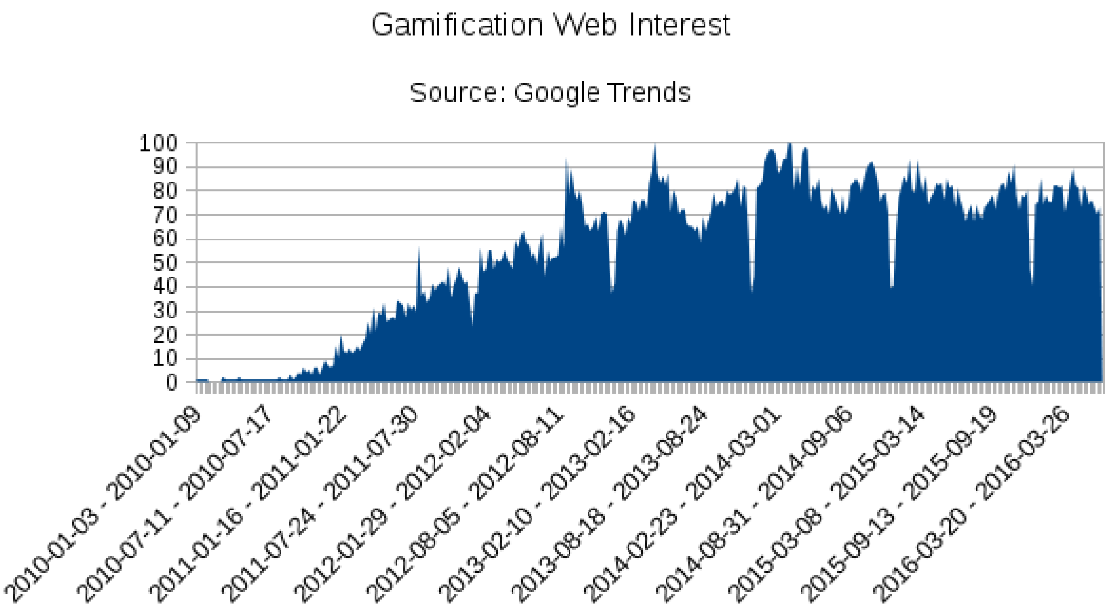

Figure 2.3: Gamification Web Interest. Source Google Trends [45]

2.3.1 Game Elements

There are several definitions depending on the author. According to Kevin Werbach [57] (Figure 2.4), the basic game-design elements are:

- *Components.* The most specific items in every game or gamified system: achievements, badges, points, leaderboards, levels, teams, etc.
- *Mechanics.* These are the rules that engage all the different components into one system, the basic relations among them.
- *Dynamics.* It is the result of putting mechanics to use. A *flow* is created between the different interactions resulting in positive or negative effects, like winning or losing.

Hunicke et al. consider that *Aesthetics* is another extra step in the top of the pyramid as the "desirable emotional responses evoked in the player, when he/she interacts with the game system" [59]. Another example is the definition found in the Enterprise Gamification Consultancy [60]. It parts from the Werbach's definition and adds to it the several items in a very formal description detailed in the following points:

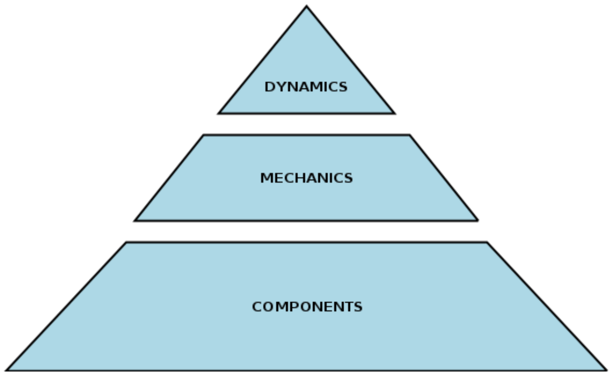

Figure 2.4: Game Elements. Adaptation from *For the Win, Werbach K.* [57]

1. *Components & Mechanics.*
2. *Dynamics.*
3. *Feedback.* It consists of a return of information to the player caused by his actions, a response of the system to interaction. This can be reflected from simple points to badges, leaderboards, levels, achievements, etc.
4. *Psychology.* It is important to know the target player's condition in order to adapt the gamified experience to his response ability.
5. *Interface.* From a simple chess table-top to a complex Android app.
6. *Aesthetics.* The art, colours, materials, design. Almost everything susceptible to personal taste.
7. *Justification/Meaning.* The purpose of the game elements beyond *Fun*, like telling a story; focus on a personal or an online experience; emulate real life (The Sims); or even informing about an issue of major concern, known as serious games (*serious games*, [61]) - the effects of drugs, the big impact of media in the world, planned obsolescence, etc.
8. *Rules.* Directly applicable to the player.
9. *Game characteristics.* They may appear either in *Layering* contexts (games in another games) or impact they may have such as becoming *viral* due to social impact.
10. *Player's Motivation.* There are two main kinds of motivation, *intrinsic* and *extrinsic* motivation. The first one comes from personal desires, strong believes or just great determination, whilst the latter comes out from outside rewards, such as points, achievements or even money. *Fun* is also another motivator that can be triggered from very different approaches like role playing, mastery and learning, social interaction or customization.

Very different gamification implementations have been found in the literature for several groups of people with good results. An extent review of different gamified apps for health related contexts and its results can be found in the paper of Pereira et al., *A review of Gamification* *for Health-Related Contexts* [58]. Some of the most relevant systems are SickKids [62], and Iphone app that helps kids with cancer deal with the pain through a western-like rol playing environment; the use of serious games scores as a health condition indicator for cancer patients [63]; *INTERACTT*, a participatory serious game design to help children with cancer in recovery fostering communication with physicians and promoting physical exercise [64]; a system for learning healthy lifestyles through active videogames, motor games and the gamification of educational activities [65]; and an interactive training in old patients with chemotherapy induced peripheral neuropathy that promotes physical recovery through the implementation of game mechanics in rehabilitation [66].

Nevertheless, there is still some controversy on its application and success. For example, the problems when applied to elder population since they are usually not very familiarized with the new technologies and game/videogame mechanics [67], or the difficulties some gamified systems can found on fostering self-confidence in an appropriate way to succeed [68, 69].

To conclude this section, I want to remark that a Coursera Gamification course given by Kevin Werbach has been taken for deep understanding of this emerging and complex subject of Gamification. See certificate in [70].

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Chapter 3

System Design & Tools

In this chapter the project's requirements are set and all the tools needed, both hardware and software, are chosen from the discussion on the different options available.

3.1 Requirements and Needs

3.1.1 Requirements

A prototype for the system proposed (see Objectives, page 10) shall cover the following requirements:

- Select an activity tracker with, at least, one day long battery duration, HR monitoring, sleep tracking and pedometer. Connectivity must be available for data storage.
- A data gathering device for parameter analysis like a smartphone.
- Development of automatic algorithms for IPAQ, ECOG and KPS inferring.

3.1.2 User's Description and Role

Two main types of users are going to interact with the system, the patients and the doctors.

For the patient, an user-friendly interface with the minimal information display is needed. The data availability will be highly restrained for these regular users. It is important not to overwhelm the cancer patient with an excessive amount of data in order to prevent hypochondriasis and apprehensive behaviour. At this point a gamified system would tackle the stimuli loop. (See Gamification. Considerations for Design, page 42)

On the other hand, for the medical personnel, all the data gathered and inferred needs to be available for displaying. According to medical advise from oncologists in the *Hospital Virgen de las Nieves*, a multiple choice view with different time-length buckets (for example, an hour, a day or a week) would be very useful.

3.2 Hardware

There is a vast and huge amount of available devices in the market related to activity monitoring, connectivity and mHealth, therefore a highly condensed summary is necessary to serve as an useful comparison instead of a deep insight on each piece of equipment.

3.2.1 Mobile Devices

Nowadays global market is having a *boom* related to activity trackers and wearable technologies. From February 2015 to February 2016 an overall growth of 171.6% in this market share has been detected. Several leading companies like Samsung, Fitbit, Apple or Sony are striving to make the most of their slice in this industry. This assures a strong range of improvements in many differently oriented sets of products: smartwatches, fitness trackers, mHealth devices and so on [1].

Moreover, the world market smartphone is still in a very good condition, delivering products for most of people. The market smartphone sales have been growing to stable within the last three years (see Figure 3.1). These are basically the same companies enrolled in the wearable industry previously commented, hence the compatibility provided among all the products is a very good starting point to take into account when building the system [2].

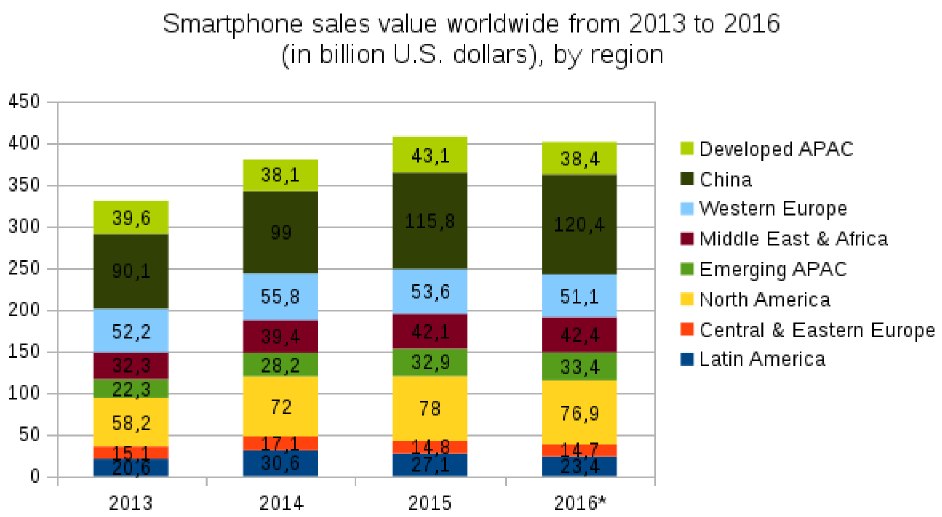


Figure 3.1: Smartphone sales value worldwide from 2013 to 2016 (in billion U.S. dollars), by region. Data source: [2]

However, there is a relevant difference in the market share of the smartphones' Operating System (OS) (Figure 3.2). Android has been controlling the market with huge prevalence since 2012. On the last record, 2015Q2, Android was running 83% of all the smartphones sold, whilst iOS was just running Apple's own devices (14% of share) and Windows Phone the 3% [3].

This is the main reason why **Android devices**, primarily smartphones, have been selected for running the biomonitoring system proposed. This project is eager to reach the most possible amount of people. This will only be possible using very popular tools like Android smartphones. There are other reasons to support Android, which will be discussed along the chapter, such as the possibility of using Google Fit and the big compatibility of the wearable industry with it (See Google Fit API, page 38).

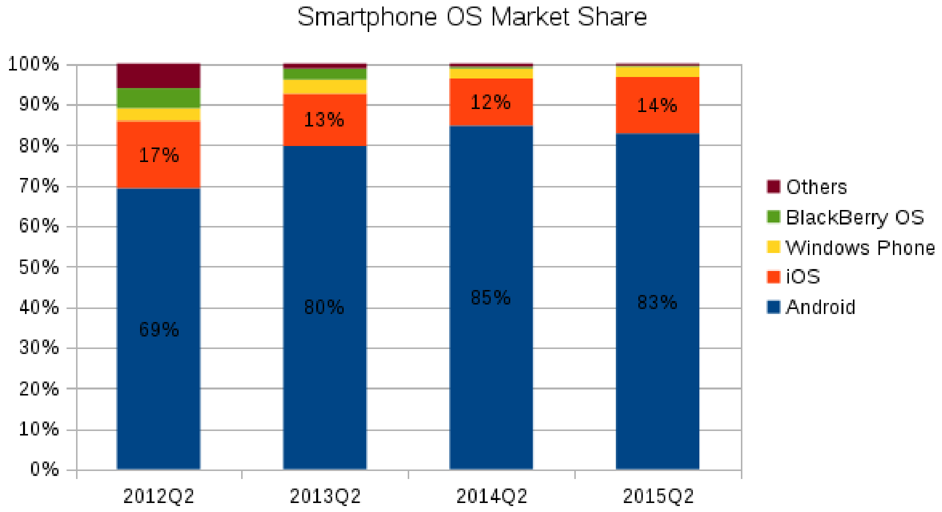


Figure 3.2: Smartphone OS Market Share. Data source: [3]

3.2.2 Wearables

Fitness assessment is the new trend for wearables. There are several companies objectively oriented to this target with diverse approaches to physical activity measurement. In this section some of the main products of the most relevant companies are going to be presented, compared and discussed for their suitability for the purpose of this project.

Smartwatches

Smartwatches emerge as the evolution of wrist watches as we knew them. The miniaturization has allowed the inclusion of powerful microprocessors along with different sensors (accelerometers, photoplethysmogram, skin temperature, etc) run by OS like Android Wear, Tizen or WatchOS 2. In Table 3.1 a summary of the Smartwach Leaders characteristics comparison is presented [4, 5, 6, 7, 8, 9].

The possible selections are highlighted in yellow whilst the reasons for rejection are clearly marked with a red N: Apple Watch and Pebble Time Round because of the lack of Android compatibility and the Samsung Gear S2 because of Tizen environment along with the absence of scheduling reminders.

Their characteristics are very similar along the different models pre-selected:

- HR measurement enabled by PPG.
- Bluetooth v4.1, LE and Wi-Fi 802.11 b/g for connectivity.
- 9-axis accelerometer, gyroscope and barometer.
- Pedometer.
- 4GB of internal storage.
- 512 MB RAM.

	Huawei Watch	Apple Watch	Samsung Gear S2	Motorola Moto 360 (2nd generation)	Pebble Time Round	LG Watch Urbane
Display Resolution (ppi)	286	326	302	233/263	191	245
Android Compatibility	Y	N	Y	Y	Y	Y
iPhone Compatibility	Y	Y	N	N	N	N
Fitness Tracking	Y	Y	Y	Y	Y	Y
Heart Rate Sensor	Y	Y	Y	Y	N	Y
Scheduling Reminders	Y	Y	N	Y	N	Y
Software	Android Wear	WatchOS 2	Tizen	Android Wear	Pebble	Android Wear

Table 3.1: Leading Smartwatch characteristic comparison

- Battery capacity of $\tilde{3}00$ mAh.

In spite of the fancy modern look the smartwatches provide, according to different Internet reviews, the performance of HR sensor in these devices is not acceptable not even for regular fitness. Besides, the cost of any of these products goes beyond 300€ , a very high cost against the low performance offered.

It is concluded that the market of smartwatches is already looking for aesthetics rather than performance, so this option seems an unlikely candidate for the prototype.

Fitbit

Fitbit offers three different products that the proposed system can rely on: Charge HR (149.95 €), Blaze (229.95 €) and Surge (249.95 €). They all meet the functional requirements of having pedometer, PPG for HR tracking, sleep tracking and long time battery duration [10].

Nevertheless, they do not provide any sort of integration with the Google Fit API, which will be key in the system proposed, gathering data only for their for their own private closed platform.

The Fitbit API is quite restricted, it enables collecting data already processed by their algorithms but it does not allow to collect it directly from the wearable. It requires the installation of their own app. Fitbit's Data Policy claims that there is complete security and privacy with the data collected and that they are not to be sold to any other company. However, they are available for making their own use statistics [11].

Microsoft Band 2

The Microsoft Band 2, with a 250$ price, suits up as a very good candidate for the project, featuring a very diverse set of sensors. It features the following characteristics:

- Battery life of 48 hours of normal use
- Optical heart rate sensor. Continuous heart rate monitoring.
- 3-axis accelerometer/gyro
- Gyrometer
- GPS
- Ambient light sensor
- Skin temperature sensor
- UV sensor
- Capacitive skin sensor
- Galvanic skin response
- Microphone
- Barometer
- Bluetooth 4.0 (Low Energy) for connectivity
- Supported mobile devices: Windows Phone 8.1 update or later, iPhone: 5, 5C, 5S, 6, 6 Plus, iOS 8.1.2, and Android 4.4 or later phones with Bluetooth
- Step tracking.

The API provided is compatible with different SDKs such as Visual Studio, Eclipse and Android Studio. It provides direct access to the sensor data in the wrist band [12].

Unfortunately, Microsoft Band does not provide any connection with Google Fit. It works exclusively with Microsoft Health Vault, which Data Policy entitles the user to adjust the data to the most strict privacy standards, even preventing Microsoft from using your data for statistics [13]. Furthermore, it is still not available for the Spanish market, which makes this item an attractive yet inappropriate solution.

Sony

Sony offers the same range of options with three activity trackers: SmartBand ROXY SWR10 (49.50 €), SmartBand 2 (129.00 €), SmartBand Talk SWR30 (159.99 €). The only with HR monitoring via PPG, (automatic and continuous manual modes available), is the SmartBand 2, so the other two devices are automatically discarded [14].

The SmartBand 2 (see Figure 3.3) meets the requirements with a very low cost comparing to the rest of devices listed. Besides, it is fully compatible with Google Fit.

Sony's Data Policy is not as restrictive as the Microsoft's Health Vault. Sony entitles itself to use the data anonymously for statistics within their company group without permission request[15]. However, for prototyping purpose this does not such an important issue to deal with.

(a)

(b)

Figure 3.3: Sony SmartBand 2 (SWR12) (a) front and (b) back.

Others: Xiaomi, Samsung and Apple

The Xiaomi Mi Finess band looks like an attractive solution due to its low cost (28$) even implementing HR monitoring with PPG. However, internet reviews reach the conclussion "you get what you pay for", even though it is very cost-effective. There is no possibility of enabling continuous HR monitoring [16].

Samsung products have been directly rejected due to the Samsung inclination of moving all its products to their own closed OS *Tizen*, therefore not assuring future consistency with the implementations developed for this prototype [17]. Apple already has this market proposal with all its products almost exclusively related to iOS and WatchOS, so the same conclusion is reached.

Conclusions

There are many different companies competing in this market, some of them may have been left behind, but an extent review of the benefits and drawbacks of the leading products have been clearly pointed out.

There is still one major issue to be addressed, common to all the brands analysed: the **medical resignation**. Each one of the activity trackers comes along with a non-warranty clause claiming that it is not a medical device. From the side of development, I want to assure that there is complete awareness of this explicit declaration, however, this is just a way for companies to tie loose ends and to leave any kind of responsibility to those who want to use the activity trackers for a medical purpose.

To conclude, comparing price, requirements fulfilment, market availability and long-term functionality, the **SmartBand 2** has been selected as the leading wearable for developing prototype in this Performance Status Evaluation Assessment System for Cancer Patients.

3.3 Software

In this section the different and new software tools adopted for this project are going to be discussed.

3.3.1 Development Framework

Android

Android counts with several frameworks for development such as NetBeans, Eclipse, both providing support for mobile and web applications in Java, Javascript, HTML5 and more [18, 19], and Google's Android Studio, which is based on the JetBrains' IntelliJ IDEA software [20].

Despite of the big documentation and guidelines already written for Android programming under Eclipse and NetBeans, **Android Studio has been selected** to develop this project since its maintainer is the same one that maintains Android, Google. At the date of writing, *Android Studio* is currently at is version 2.1.2, which has proven extremely useful due to the high integration of Android assistance: to automatically create *getters* and *setters* in a class, templates for different kind of interface views such as *Scroll View*, *Navigation Drawer* or just *blank* activities. It has also improved the *Layout Editor*, making it more accessible enabling *drag and drop* actions and giving recommendations about the *Material Design* guidelines for aesthetics [21].

Furthermore, the community is already migrating to this platform due to the high support Google is giving. New publications from known publishers such as *Big Nerd Ranch* are already using Android Studio for development, courses and books like the one I used as the main guide through the project, *Android Programming, 2016 Edition* by Bill Phillips et al. [22].

Data Post-Processing & Algorithms

There are diverse tools to implement the data post-processing, languages like C, Java, R, Octave or even MATLAB. In this case, and for the project's prototype, **MATLAB has been chosen** as the framework to apply the algorithms to the gathered data. MATLAB is a development platform optimized to resolve engineering and science problems. Its language is based on matrixes and it provides integrated graphics to display the data accurately. Besides, there is available a vast library of toolboxes that enables immediate work with specific algorithms in areas like signal processing or statistics[23]. Moreover, MATLAB is a tool that has been used all along the Bachelor's Degree in Industrial Electronic Engineering and it is known fairly well to start obtaining results with the comfort that the rest of very new areas like Android programming might not provide.

3.3.2 Object-Oriented Programming

Android development is mainly done in Java, so this comes with a new programming paradigm never tackled before in the Bachelor's Degree of Industrial Electronics Engineering, Object-Oriented Programming (OOP).

OOP is based on the concept of *objects* that may contain data within its *attributes* (like fields). These *objects* are defined with *Classes*, in the class-based languages, that may also contain *methods* in which procedures are declared. The objective is to make the different *objects* interact among them via the *methods* defined in each one. The class-based languages create *objects* as instances of classes. The main reference for OOP learning has been the book from López Goytia et al., *Programación orientada a objetos C++ y Java: un acercamiento interdisciplinario* [24] and web resources like StackOverflow [25].

Objects and Classes

It is usual that OOP languages support inheritance for code reuse and extensibility via other classes. The two main concepts of objects are classes are closely related:

- **Class.** It is the definition for the available data and methods (or procedures) for the given object. It is like the archetype from which objects can receive its characteristics, e.g., the `Animal` class.
- **Object.** They are instances of classes. For example, the objects `lion` and `cat` can be created as instance of the class `Animal`.

Classes define variables, known as *fields*, and methods. Depending on their relationship with the objects inherited, different classification is accepted:

- **Class variables.** They belong strictly to the class, regardless of how many instances exist. These variables are normally declared as `static`.
- **Instance variables.** The field is defined in the class but each instance may have its own value in it.
- **Class methods.** The methods declared belong to the class. These methods are normally under complete data request for they to properly work. For example, the method `public static double sum(double num1, double num2)` allocated in the `Operations` class.
- **Instance methods.** These methods are applicable directly to the instance created. They cannot be executed for the class itself. It could be the method `run()` executed for the instance `cat` with the command *cat.run();* .

SOLID Guideline

In order to create maintainable code for the application designed, the SOLID principles have been taking into account [26, 27]. Other guidelines like GRASP are famous but no explanation for Android was found.

SOLID is a mnemonic acronym that helps define the five basic object-oriented design principles:

- **Single responsibility principle.** A class should have only a single purpose or responsibility, like handling the patient's data.
- **Open/close principle.** Classes should be open for extension but closed for modification. High modification of classes for new features may point out a bad design.
- **Liskov substitution principle**. Objects in the program should be replaceable with instances of their subtypes without altering the correctness of the program. For example, a method to run an `Animal` object should not have a problem to run a `Mammal` that extends `Animal`.
- **Interface segregation principle.** Different specific interfaces are better than one general-purpose interface.
- **Dependency inversion principle.** Classes and programs should depend upon abstractions and not upon concretions.

3.3.3 Google Fit API

Due to the high market share that Android has over its competitors, most of the wearable and fitness tracking devices implement connectivity with Google Fit. The election of Google Fit for data collection allows for data management for a high number of different activity trackers and wearables in the market.

High difficulties have been presented when dealing with this API due to the lack of accurate documentation's distribution all along the Guides, Reference and Developers sites for Google Fit. Besides, since it is still a rather early technology there is not much help on forums like StackOverflow – at least beyond the most basic implementations which are available in the official Google Fit website too. There are two APIs, the API for Android and the REST API for implementation in other devices[28].

Since the project app is android-oriented, the API for Android has been further studied and it is detailed in the following subsections. Its structure can be seen in Figure 3.4.

3.3.4 DataSources and DataTypes

Google Fit defines DataSources and DataTypes for treating DataPoints. When DataPoints gather in DataSets, they always refer to a DataSource and to a DataType to know exactly what they are.

DataSources are the definition for the origin of the data. For instance, in this project, two DataSources can be found: the smartphone data and the Sony SmartBand 2 SWR12.

DataTypes define the format of the values inside the DataPoints. This format can be:

- An instantaneous reading or observation, the *TYPE_* DataTypes.
- An aggregate with statistics over a time interval, the *AGGREGATE_* DataTypes.

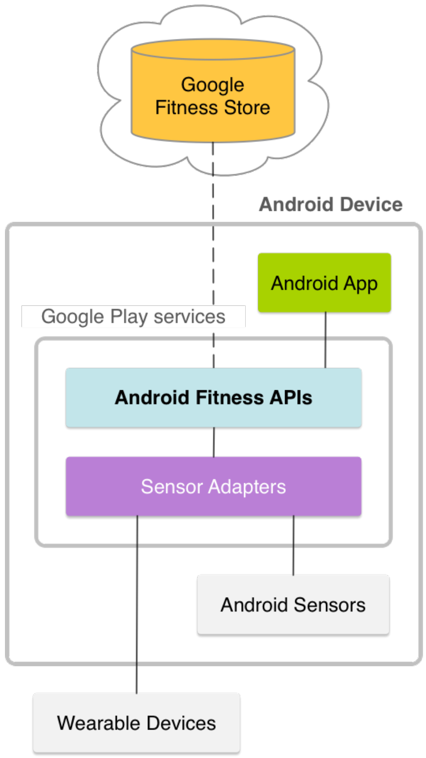


Figure 3.4: Google Fit on Android. Source: [28].

All the available DataTypes can be foun in the section Google Fit's DataTypes of the Appendix, page 91 [28].

Sensors API

Sensors API exposes different sources of fitness data in local and connected devices, delivering also live events to listeners. It is primarily oriented for data displaying in real time.

It can handle different DataTypes from different DataSources and pick up the better option automatically. For example, the steps counting when wearing smartphone and the Sony SmartBand 2 automatically selects the best measure obtained.

Recording API

Recording API allows for enabling low-power, persistent and always-on background collection of sensor data into the Google Fit store. These *subscriptions* are active when the app is not running and through system restarts. The collected data can be queried later using the History API. Recording API does not support delivery of live sensor events, unlike Sensors API.

History API

History API is for inserting, deleting and reading data in Google Fit.

The `readData(GoogleApiClient, DataReadRequest)` is used when historical data is needed. It should have been recorded with the Recording API and its corresponding subscription listeners. In the `DataReadRequest` the *DataTypes* requested should be specified in a properly defined time, for example, the Steps Count of the previous hour in time-buckets of 5-minutes.

The `insertData(GoogleApiClient, DataSet)` is for including data collected outside of Google Fit. This allows the system to be used with completely personalized devices, maybe for further research or for using devices in the market that do not support Google Fit connection.

Sessions API

Sessions API is for creating and managing sessions of user activity in Google Fit. This is an easy way to display information in the Google Fit environment.

Methods `startSession(GoogleApiClient, Session)` and `stopSession(GoogleApiClient, String)` enable automatic session recording. It need the HistoryApi inserting data to its record.

Sessions can be inserted or deleted with the methods `readSession(GoogleApiClient, SessionReadRequest)` and `deleteData( GoogleApiClient, DataDeleteRequest)`.

BLE API

BLE is named after Bluetooth-Low-Energy. This session is for scanning, claiming and using BLE devices in Google Fit. It should be used in case a personalized or non-Google-Fit-compatible device is presented.

Config API

Config API is for accessing custom data types and settings in Google Fit. Custom data types are created when the available are not appropriate for the signal monitoring purposes.

They can be created with the method `createCustomDataType( GoogleApiClient, DataTypeCreateRequest)` and later be used on the rest of APIs normally, for it to be shown (Sensors API), registered (Recording API) or recorded/read (History API).

3.3.5 Android Threading

For automatic data query, the following Android classes and methods have been studied [29].

AsyncTask

AsyncTask enables a proper and easy use of the User Interface (UI) thread. This class allows to perform background operations and publish results on the UI thread without having to manipulate threads and/or handlers.

This is a very useful tool for background operations while the app is being actively executed and there is interaction with the user, however, this class only served for debugging purposes and to make instantaneous queries instead of programmed. It is recommended for short operations, a few seconds at the most.

An asynchronous task is defined by three generic types, called `Params`, `Progress` and `Result`, and four steps, called `onPreExecute`, `doInBackground`, `onProgressUpdate` and `onPostExecute`. The main type is the `doInBackground` in which the program to execute is defined.

Services

A service is an application component that can perform long-running operations in the background of the Android system and it does not provide a UI.

To create a service it is necessary to create a subclass of Service in the implementation. Then, it is necessary to override some callbacks to handle the key aspects of the service lifecycle. The most important callback methods are the following:

- `onStartCommand()`. The system calls this method when the service is requested to be started.
- `onBind()`. The system calls this method when another component wants to bind the service.
- `onCreate()`. The system calls this method when the service is first created.
- `onDestroy()`. The system calls this method when the service is destroyed.

It is necessary to declare the services used in the Manifest file.

```
<manifest ... >
  ...
  <application ... >
      <service android:name=".ExampleService" />
       ...
  </application>
</manifest>
```

However, there is an implementation based on **IntentService** that is used when the service does not need to handle multiple requests simultaneously. It makes this choice ideal for data querying. The IntentService does the following:

- Creates a default thread that executes all intents delivered to `onStartCommand()` separate from the application's main thread.
- Creates a work queue that passes one intent at a time to the `onHandleIntent()` implementation.There is no need to worry about multi-threading.
- Stops the service after all start requests have been handled. No need to call `stopSelf()`.
- Provides default implementation of `onBind()` that returns null.
- Provides a default implementation of `onStartCommand()` that sends the intent to the work queue and then to your `onHandleIntent()` implementation.

Finally, to schedule automatically the querying in time, **AlarmManager** is used. This class provides access to the system alarm services and to schedule applications to be run at some time in the future. The Intent registered is automatically broadcasted by the system. To implement this, the IntentService is registered within the AlarmManager with the method `setServiceAlarm(Context, BooleanIsOn)`.

3.3.6 Database Storage

For database storage various technologies were firstly proposed from all the known in the market such as MySQL, Oracle and SQLite [30, 31, 32]. As this first approach to the system has a very reduced time for development, **SQLite has been selected** as database technology since it is a local database very well implemented within the Android developing framework. On the other hand, MySQL and Oracle need of remote sever and a more complex implementation that goes beyond the purpose of this project prototype.

For the SQLite management with MATLAB the library mksqlite has been used [33].

3.4 Gamification. Considerations for Design

The inclusion of gamification in the design aims for improving cancer patients' recovery and creating a patient-oriented system. It has been carefully designed always following the recommendation from psychologists in the Hospital *Virgen de las Nieves, Granada*; the psychological condition of patients found in the literature [34, 35]; and the gamified projects already done reviewed in the *State of the Art* (page 14). An early version of this design was already published in the International Work-Conference on Bioinformatics and Biomedical Engineering (IWWBIO) 2016 [36].

3.4.1 Cancer patients' psychology

The patient develops a series of cognitive and behavioural responses to the treatment always from a cognitive triad: diagnostic vision, sense of control perceived and prognosis vision. Five facing styles are found: Fighting Spirit, Avoidance/Denial, Fatalism/Acceptance, Hopelessness/Abandonment, and Anxious Concern [34].

According to the studies found in the literature [37, 38], there is prevalence of Fighting Spirit along with moderate information research and ocassional Denial. However, one of the problems found with cancer patients' psychological condition is that society does not tolerate any sight of depressing moments for theirselves, they cannot show any weakness in their recovery. Nonetheless, these moments are very necessary for their recovery and it is part of their defense behavioural mechanisms. Facing cancer is already a big pressure, so people or a biomonitoring system should not add more but just to understand the necessary emotional stages of the patient [34].

3.4.2 Gamification Objectives

The main objective is to **improve the recovery of cancer patients**. The use of game-elements along with the biomonitoring system will be focused to **leverage both patient's extrinsic and intrinsic motivation**. For this, a closed social network where patients with the highest KPS scores (60-100) and medical personnel is proposed. This will provide each member a strong sense of relatedness and confidence as part of a very significant community. Optional open social media with tools like Twitter or Facebook are also foreseen.

Although patients' closed network may only be available for those with higher recovery prospectives, the rest of the framework would be available for everybody. The tools provided will focus on **delivering a sense of empowerment and autonomy** to every patient. One of the keys to enhance intrinsic motivation of patients is to give them back some control of their treatment. Just waiting for diagnosis and analysis may be very harmful in a psychological way, so the gamified app will highlight all the achievements made by the patients on their own, such as fulfilling the quests given and remarking on the physical activity done during a day.

To **promote physical activity** is another objective. The gamified system will make the most of quests and missions by encouraging patients to stay in touch, to move through different rooms of the house, to ask for information, to gather people together, and so on, everything in a game-like environment.

To **provide feedback for the doctor and developers on the app use**. The application is not going to focus strictly on the different kind of cancer that may appear, however, it will give the patient a weekly questionnaire to explain what kind of troubles or pains has he faced. Statistics on the use of the application will be used for development.

To have **fun** when using it. Fun is the most important key element of engagement to the patients like in every game. They must be having a good experience thanks to the app. For example, the system will give tags every day with different animals according to the performance done, like as a resilient horse with boxing gloves or a brave athletic lion – for a very good performance –; or a lazy sleepy jaguar – for a sudden drop in activity.

3.4.3 Target Behaviours

One of the major problems of facing cancer is the treatment. Chemotherapy and radiotherapy cause both a long set of side effects which can lead the patients to reduce their physical activity due to the depressive state and the fatigue acquired. So, in order to beat these drawbacks we want players to:

- Do more physical activity. Movement will be attached to most of the activities guided by this app.
- Do regular check-ins in the app delivered.
- Keep track of the personal progress thanks to the data collected and the badges earned. Some of the data measured are the following.
- Stay in touch more regularly with other patients through the exclusive and closed social network provided.
- Keep using the gamified system for the whole recovery simply because they want to, because they feel there is something good for them in the mechanics applied.

3.4.4 Players Description

Patients

The system is focused on patients **sharing the same objective, beating cancer**. Thus, a group of people fighting against the same kind of problems related to cancer and its treatment is being considered. Patients affected by cancer cover the whole range of possible ages, however, there is a higher amount of elder than young people in the balance. The application is designed to fit every kind of patient willing to beat cancer, but we are aware that younger people (below 30-40 years old approx.) are going to find the gamified app easier to interact with it since they have grown in a world where videogames and computers are everywhere. So, the solution, is to make the community conformed interact in real life, specially with the medical personnel.

Medical Personnel

Doctors, nurses and psychologists are also participants of the system, so the system will provide data of the performance of each patient individually. This is feedback for the medical experts, objective data of the biomeasurements gathered and subjective data from the written feedback of the patients. Physicians will be also key to integrate elder patients within the community the game mechanics create.

3.4.5 Activity Loops

Engagement Loop

Engagement is necessary to make patients feel comfortable from the beginning, so the first use should be guided and very intuitive. Then the engagement loop can work on its own (Figure 3.5a). This loop is the one that keeps the patient activated around the system, triggering the loop stimuli in each notification of badges, points and achievements.

For the **onboarding**, in a introductory session of the benefits of making physical activity, social activities and positive thinking to fight cancer will be explained. Then, this gamified system will be introduced as a way to make this in a very easy way. It will be informed also that the biomonitoring device will gather continuous data from the patient to provide objective measures to the physicians.

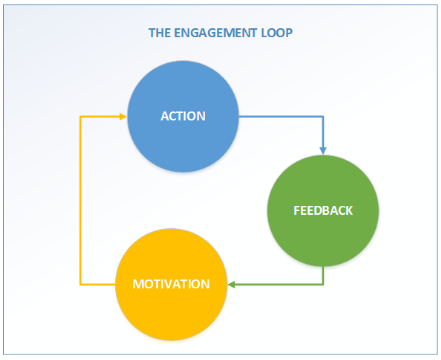
The **scaffolding** consists in starting the engagement loop. On the first use, a patient account will be requested to access the app. Then, an assistant will guide the patient through the different quests, missions and tasks to do. Charts and diagrams will give the information of the different available and realised achievements. There will be also a wall where the badges attached to your achievements are collected. This is a very powerful way for the patients to keep track of the progress just from a glance. Doctors will also give surprise badges for every good analysis and after any clinical test or review.

Progression Loops.

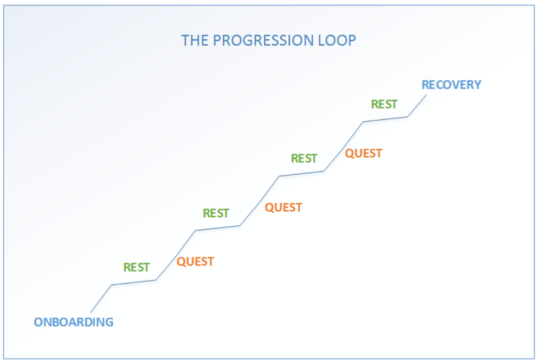
Progression is this intangible sense of advance you feel when looking backwards at any point in your life (Figure 3.5b). The elements described before, quests, missions, badges and achievements are going to make this possible and in a very easy way. This activity tracking will be easily accessible for the patients to see their own progress, always highlighting the good results on the tendencies. Besides, there will be different experience points attached to each kind of activity:

- Physical activity: referred to the time stood up, the steps given or the intensity of activity performed in a certain time.
- Social activity: referred to activities involving social interaction. This will be very important in the social framework for the social community of patients.
- Mental activity: referred to quests and missions that imply concentration activities.
- Reflexive activity: referred to quests and missions that imply deep insights.
- Emotional activity: referred to quests and missions that are related to the own or other people feelings.

Moreover, like in videogames, the patient will be able to beat **final bosses**, for example, when they pass a chemotherapy, radiotherapy or reduce the tumor volume. This will also be shown in the patient's profile, highlighting progress again.



(a)



(b)

Figure 3.5: (a) Engagement and (b) Progression loops. Adapted from [39]

Fun

Like every game, a gamified app should come with fun attached to the process. The fun comes along with all that was described before: the sense of progression, being part of a community and beating cancer together.

A fine art is needed to make the system app attractive for both smartwatches (in case) and smartphones: charts, figures, interface, enjoyable pictures of funny animals that describe the patients, personalized avatars, etc.

Game-design Elements and Tools

To achieve all this, the following tools are necessary:

- *Quests.* Missions or objectives for the patient to fulfil. They will be all related to health and physical activity. In Figure 3.6 a first approach to its implementation in the Android app of OncoHealth has been done. To activate the activity the user would only need to press on them to increase the counter.
- *Badges.* Achievements to earn in determined conditions, for example, for good physical activity performance in IPAQ score, for giving more than 10 000 steps in a day or for maintaining a good tendency all over the week.
- *Social media.* This will enable build-up of a community where patients can fight in group.
- *Points.* Physical, Social, Mental, Reflexive and Emotional points attached to any activity.

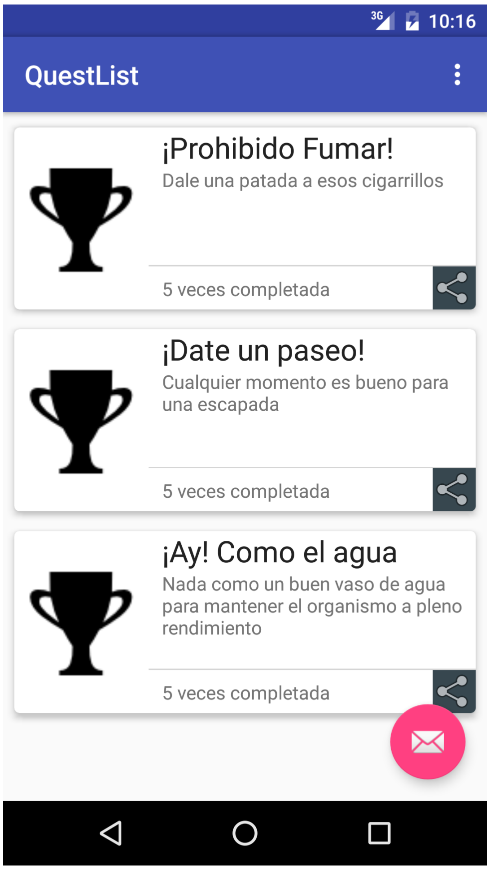


Figure 3.6: Quest list in an Android ScrollView design

3.5 Summary & System Design Overview

After knowing all the parts involved in the system, now it can be depicted in a general diagram in Figure 3.7. It combines all the elements chosen and discussed along the chapter in a solid design implemented in Chapter 4.

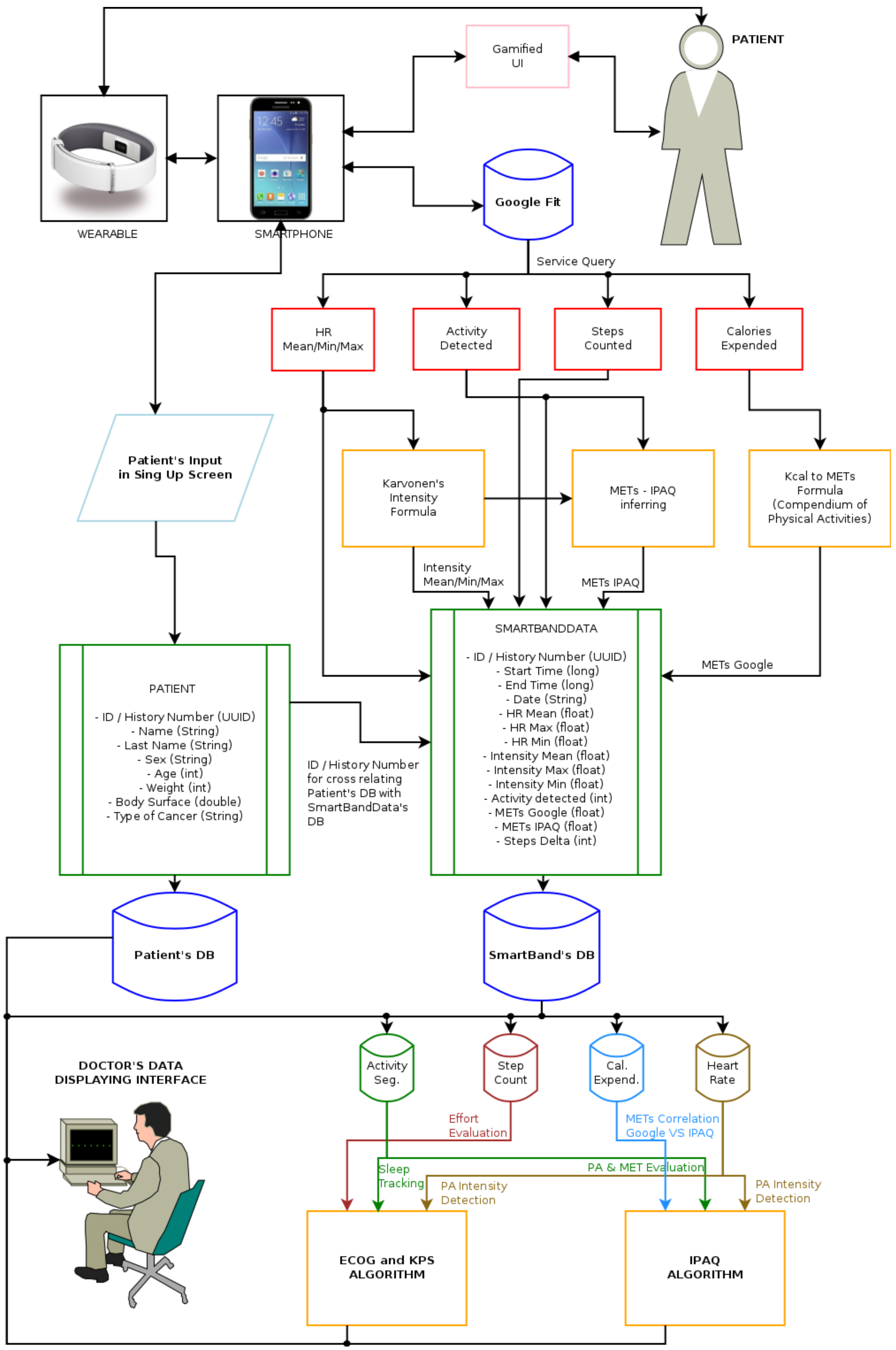


Figure 3.7: General Schema of the complete System proposed

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Chapter 4

System Implementation and Results

For all the implementation the following devices have been used:

- Sony SmartBand 2 (SWR12) for biomonitoring. Brand new and specifically acquired for its implementation in the system.
- Samsung Galaxy ACE 2 (GT-I8160). Three-years-old mid-range personal smartphone. Running Android 4.4.4 - CyanogenMod.
- Personal laptop ASUS K53SJ running Debian Jessie 8.5; MATLAB version R2013a.

4.1 Patient's App

First of all, it is necessary to select the data to be collected, then implement it into an app based on the Recording API from Google Fit. Then the History API can be implemented into a service to query and pre-process the data requested. This will be pursued with two different apps, **OncoRecord** and **OncoHealth**, which will be in-depth explained along the chapter.

4.1.1 Data Recorded

To infer the IPAQ (see subsection 4.2.1, page 65), and the ECOG and KPS (see subsection 4.2.2, page 68), the following data is required to be queried from the Google Fit API. A structure of the data purpose can be seen in Figure 4.1:

1. **Heart Rate** (*DataType.TYPE_HEART_RATE_BPM*). HR can be monitored in two different modes, automatic and manual. In this project the automatic mode has been selected due to the following reasons:
    - The automatic mode is entirely controlled by the SmartBand 2. According to the tracking and the experiments done, it tracks HR for 1 minute long after time intervals between 2 and 15 minutes, depending on the activity detected by the accelerometers of the wristband. Consequently, a non-regular sampling will force a post-processing to enable comparison with other measures. In this mode battery lasts for 48 hours long. The automatic activation of HR monitoring when sudden activity is detected makes this option suitable for the purpose of measuring tendencies and patient's state

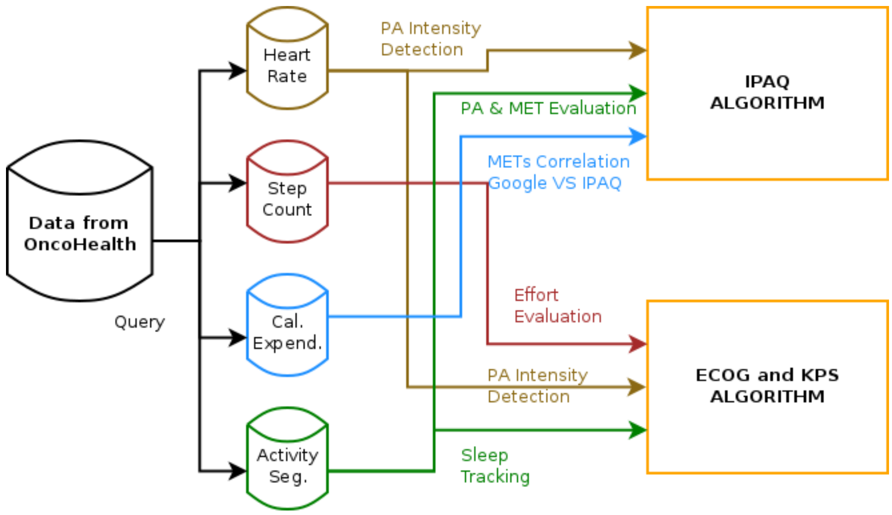


Figure 4.1: Data Structure and utilization in IPAQ, ECOG and KPS algorithms.

differences along the time. For example, if the wristband user is in a still position, the monitoring will be activated in time intervals of 15 minutes; if suddenly he starts walking or moving, the SmartBand 2 will automatically start to measure HR.

- The continuous mode is controlled by the user, activated manually by double clicking the button on the side of the wristband. Thereon a more reliable measure is gathered at the expense of reducing the battery duration to max of 16 hours. The reason this mode is not selected is double, first because there is no need for that size of accuracy when monitoring for entire weeks long, and second because the battery draining is too high.

2. **Step Count** (*DataType.TYPE_STEP_COUNT_DELTA*). Step Count has a continuous sampling frequency determined by the hardware itself. It combines data from the accelerometers of all the devices being carried (smartphone, wearables, tablet...) thanks to the Google Fit technology. Thus data will be ultimately bucked in length segments as requested in the app, in this case 5 minutes, as explained in subsection 4.1.4 *OncoHealth*, page 57.

3. **Calories Expended** (*DataType.TYPE_CALORIES_EXPENDED*). These data is used to compare the MET activity measured with the IPAQ criteria against the Google Criteria. In subsection 4.2.1 *MET for IPAQ*, page 66 will be concluded the good scoring of IPAQ criteria and the inclusion of Resting Metabolic Rate (RMR) of Google Calories estimation.

4. **Activity Segments** (*DataType.TYPE_ACTIVITY_SEGMENT*). Activity recognition is primarily done by the response of accelerometers and HR monitoring. This enables to recognise still, walking, running, cycling and sleeping conditions that will be used for the IPAQ and KPS-ECOG algorithms.

4.1.2 Authentication & Authorization system

In order to get access to the data in Google Fit repository, an OAuth 2.0 Client verification is needed for the app.

For prototyping purpose, it has been chosen the **Debug Certificate** over the Release Certificate process to put the system to work. It is necessary to:

1. Locate the debug keystore file, usually located in the same directory as the AVD.
2. List the SHA-1 fingerprint entering the following command:

```
keytool -list -v -keystore ~/.android/debug.keystore
-alias androiddebugkey -storepass android -keypass android
```

3. Introduce the Credential into the Google Developer Console (Figure 4.2).

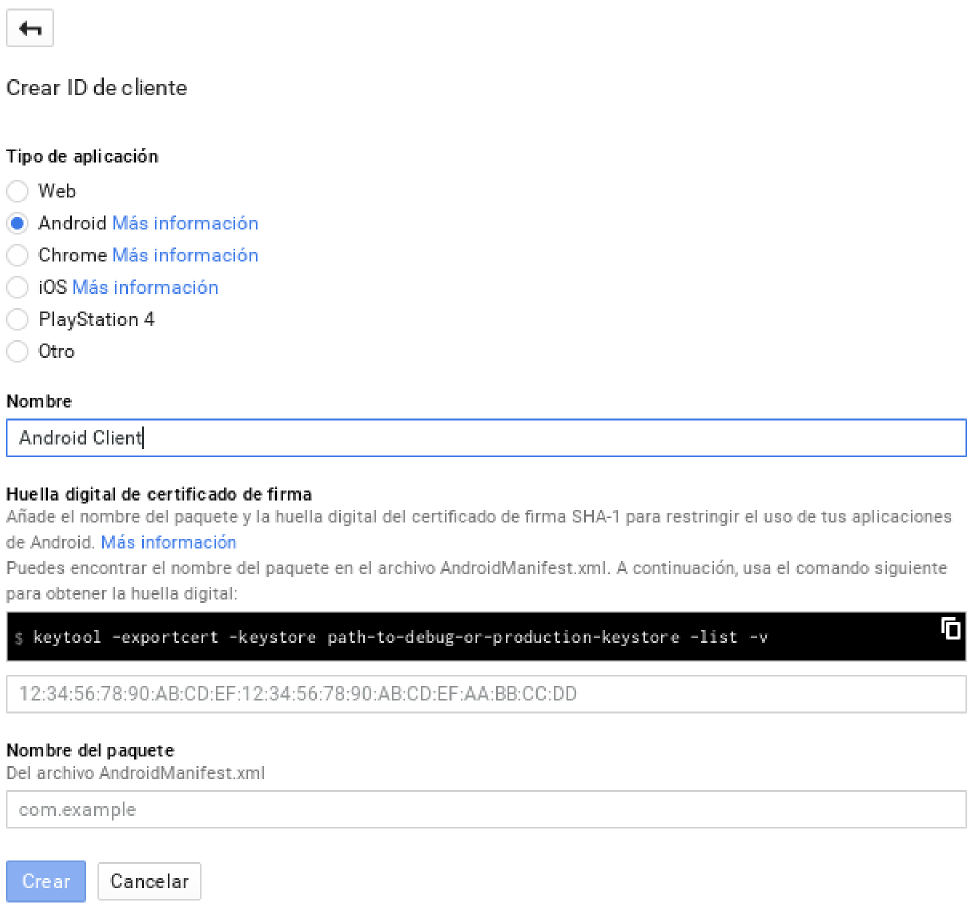


Figure 4.2: Google Developer Console OAuth 2.0 Certificate Request.

4.1.3 OncoRecord

First of all, it is necessary to start the automatic recording of the data selected. For this, the **Recording API** in Google Fit has been used. Along this subsection the issues tackled to make this happen are going to be explained. In the Figure 4.3 the following codes referred to permissions and dependencies are summed up.

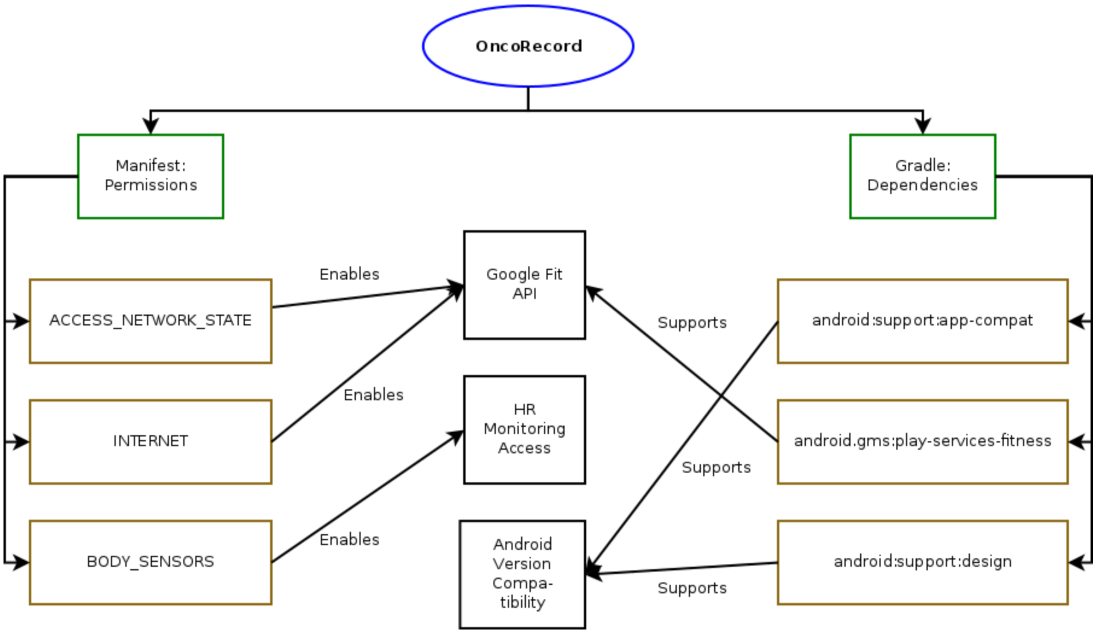


Figure 4.3: Permissions and Dependencies declared in OncoRecord.

Android Manifest: Permissions

In the Android Manifest are summarized the main components of the app such as its name, activities, services, permissions, intent-filters and so on. For this app the following code refers to the permissions required by the app:

```
<manifest package="es.ugr.smoreno.oncorecord"
        ...
<uses-permission android:name=
        "android.permission.ACCESS_NETWORK_STATE" />
<uses-permission android:name="android.permission.BODY_SENSORS"/>
<uses-permission android:name="android.permission.INTERNET" />
 ...
</manifest>
```

ACESS_NETWORK_STATE allows network connection status checking, BODY_SENSORS allows recovering data from HR monitoring and INTERNET allows internet connection to the servers in Google API and checking internet status.

Gradle: Dependencies

In the Gradle file the compiler settings are disposed, where the minimum and the maximum Android versions , the dependencies and the package name are defined. For this app the minimun SDK version is 18, that is Android 4.3 Jelly Bean, which is the minimum requisite of the wearables discussed before to interact with it. In the following code important dependencies are listed:

```
dependencies {
    compile fileTree(dir: 'libs', include: ['*.jar'])
    testCompile 'junit:junit:4.12'
    compile 'com.android.support:appcompat-v7:23.4.0'
    compile 'com.android.support:design:23.4.0'
    compile 'com.google.android.gms:play-services-fitness:9.0.1'
}
```

In the dependencies, 'com.android.support:appcompat-v7:23.4.0' and 'com.android.support:design:23.4.0' are for backward compatibility of the most recent features in the previous versions of android. The package 'com.google.android.gms:play-services-fitness:9.0.1' includes the necessary for working with the Google Fit API. It is very important to only include the necessary packages to not overburden the app. For example, if the project were to include the whole 'com.google.android.gms' package without specifying the play-services-fitness part, it would be impossible for the device to even start the app.

Main Thread: Data Subscriptions.

The main thread or activity running in this app consists of **starting up the data subscriptions** with the Google Fit Recording API (Figure 4.4). The activity is entirely separated in other app due to the importance of avoiding interferences when using different Google Fit APIs at the same time. Besides, the subscriptions are persistent, that is, they remain active despite of reboots, battery drains or simply using the phone. This has been very useful for debugging purposes, not interrupting the Recording API after every OncoHealth reinstall. The key part of the code in the 'MainActivity.java' is the following:

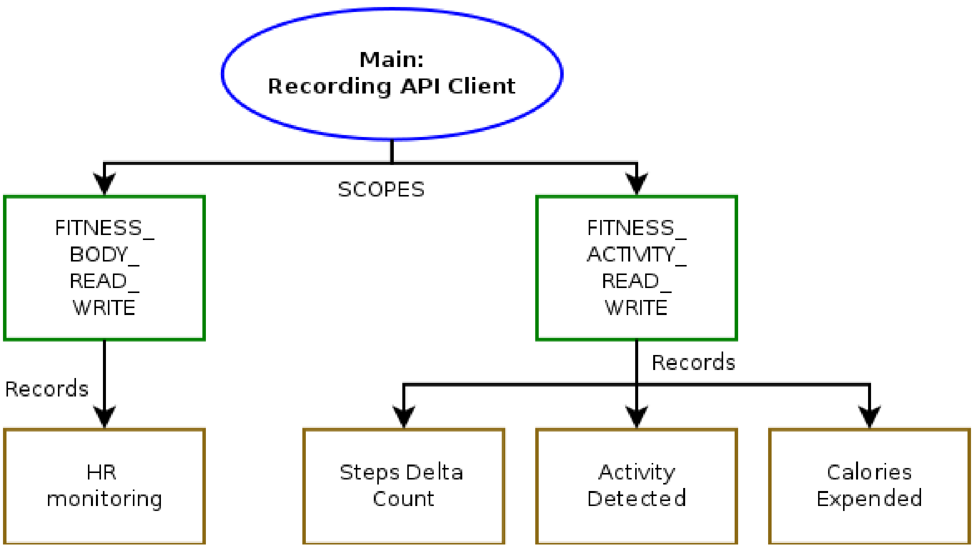


Figure 4.4: Recording API implementation in OncoRecord's main activity.

```
private void buildFitnessClient() {
        // Create the Google API Client
        mClient = new GoogleApiClient.Builder(this)
                .addApi(Fitness.RECORDING_API)
                .addScope(new Scope(Scopes.FITNESS_BODY_READ_WRITE))
                .addScope(new Scope(
                        Scopes.FITNESS_ACTIVITY_READ_WRITE))
                .addConnectionCallbacks(
                        new GoogleApiClient.ConnectionCallbacks() {

                            @Override
                            public void onConnected(Bundle bundle) {
                                Log.i(TAG, "Connected!!!");
                                // Subscribe to some data sources
                                subscribeHR();
                                subscribeActivitySummary();
                                subscribeCaloriesExpended();
                                subscribeStepCountDelta();
                                subscribeActivitySegment();
                            }

                            ...
                })
                .build();
    }
```

It is executed in the *onCreate()* part of the program execution. First, the Google API Fit client is created and then the Recording API is added. Next, two important *Scopes* are defined for the sake of the data gathering:

- Scopes.FITNESS_BODY_READ_WRITE for HR monitoring permission.
- Scopes.FITNESS_ACTIVITY_READ_WRITE for obtaining activity, steps count and calories expended.

Then, on connection, each subscription is activated. Once it is working and firstly executed, the data starts getting recorded automatically. The next code is an example for HR monitoring, which can be applied to any of the data types required:

```
public void subscribeHR() {
// Start subscription to dataType
Fitness.RecordingApi.subscribe(mClient, DataType.TYPE_HEART_RATE_BPM)
        .setResultCallback(new ResultCallback<Status>() {
        @Override
        public void onResult(Status status) {
        if (status.isSuccess()) {
                if (status.getStatusCode()
                == FitnessStatusCodes.SUCCESS_ALREADY_SUBSCRIBED) {
                Log.i(TAG,
                "Existing subscription for activity detected.");
        } else {
            Log.i(TAG, DataType.TYPE_HEART_RATE_BPM.toString() +
            " successfully subscribed!");
            }
                } else {
                Log.i(TAG, "There was a problem subscribing.");
            }
                }
        });
// END subscription to dataType
}
```

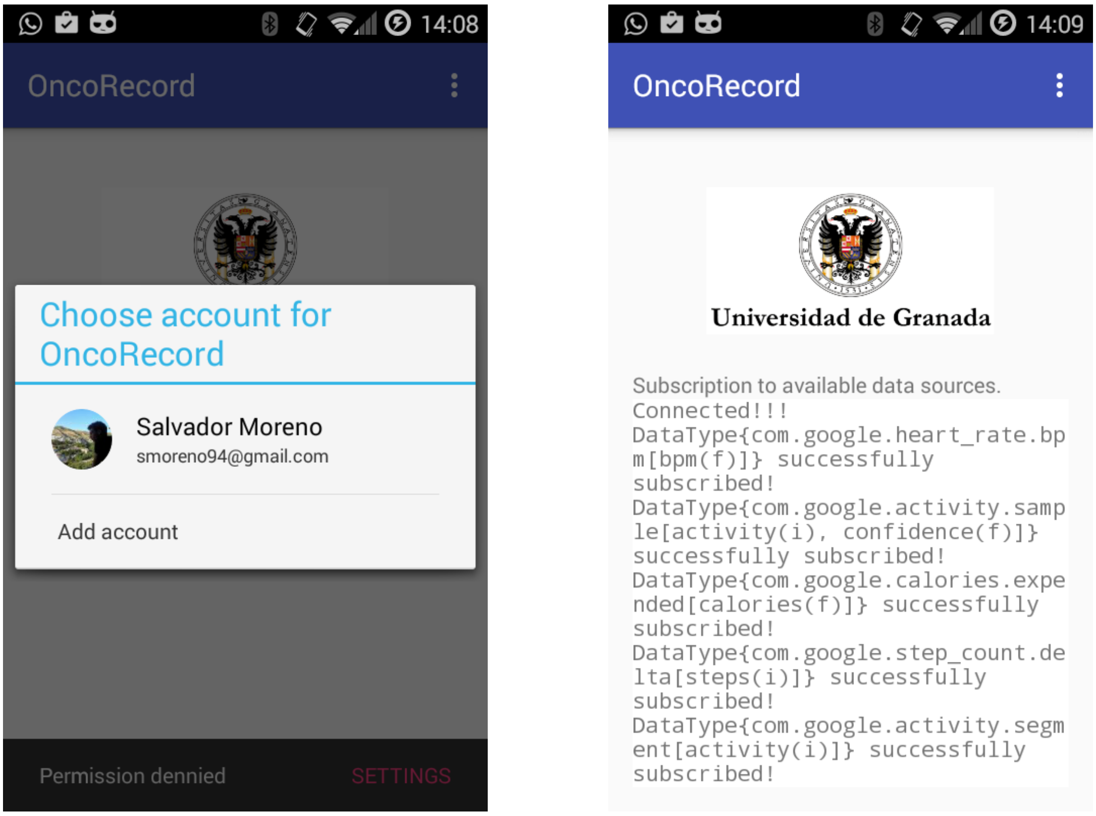
ScreenShots

In the Figure 4.5a the request of permission generated by the OAuth2.0 certification can be seen. It will only require for the first time used or if reinstalled. Before the permission is given, it is checked. That is why there appears a *Snackbar* claiming the denial and also why the formal request is displayed.Once accepted, the subscriptions are successfully activated and ready to monitoring data continuously (Figure 4.5b).

4.1.4 OncoHealth

OncoHealth app is primarily focused around the Google Fit **History API** that queries the necessary data relevant for the patients' evaluation. This API works by bucketing the continuous data collected by the subscriptions activated in the OncoRecord app in long-time data buckets. The app also makes some pre-processing and data inferring of the data due to the way Google Fit queries back the data, always associating the data to the patient logged in the app.

At this moment it is important to meet a compromise where the sampling frequency of the data collected needs to be enough and relevant to obtain successful results. According to the data sampling frequencies, specially the HR monitoring, it is irrelevant to measure faster than every 2 minutes since it is the maximum in automatic mode.



(a) (b)

Figure 4.5: Figures of (a) OncoRecord asking for Google Fit Data access permission and (b) OncoRecord activating subscriptions successfully.

Finally, after several study and performance outcome, it was concluded that there was no difference between using a sampling time of 2 minutes and using 5 minutes. Thus, **a 5 minutes bucket time** has been used.

Here it is reminded the importance of measuring tendencies and progression of the patient, that is, along hours, days and weeks. The diagnosis inferred in with the data is based on the big picture, on the evolution of data, specially when the medical personnel study it. It is important for the doctors to highlight the evolution of patients before and after treatment both short and long term.

OAuth 2.0, Manifest & Gradle: Permissions and Requests

As in OncoRecord, this app needs for OAuth 2.0 credential to work propperly. The same steps are followed to include the package in the Google Developer Console. Besides, there no need of special permissions to be declared in the Manifest. The Gradle remains with the same properties as OncoRecord (Figure 4.4).

Main Activity

On the first use two things are going to be needed: **to insert the patient's data** and **to give permissions** for querying the data with the History API. This will result in the activation of a *Service* to query the recorded data every hour.

The app is built around the two major objects: the **Patient's object**, with all the necessary information to identify the subject, and the **SmartBand-Data's object**, with all the pre-processed information obtained from the History API query. The whole process summarized in Figure 4.6 will be activated every hour thanks to the *Service* installed.

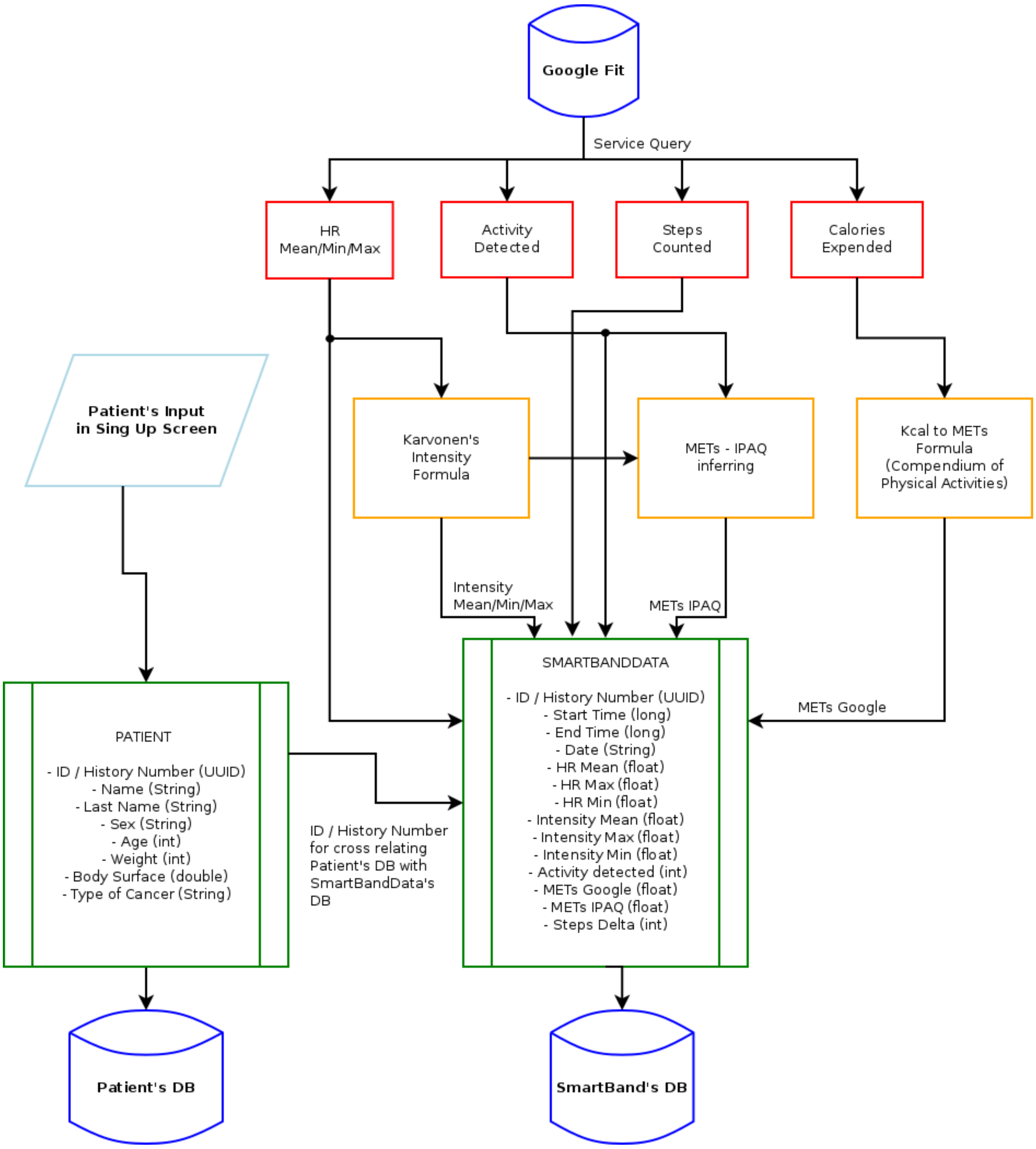


Figure 4.6: OncoHealth main activity flowchart.

The obtention of the data from Google Fit has been done with the **History API**. In the *DataReadRequest* prepared, the raw data of the previous hour is aggregated in time buckets of 5 minutes thanks to the following code:

```java
public static DataReadRequest queryFitnessData() {

    Calendar cal = Calendar.getInstance();
    Date now = new Date();
    cal.setTime(now);
    long endTime = cal.getTimeInMillis();
    cal.add(Calendar.HOUR_OF_DAY, -1);
    long startTime = cal.getTimeInMillis();

    DateFormat dateFormat = getDateInstance();
    DataReadRequest readRequest = new DataReadRequest.Builder()
        .aggregate(DataType.TYPE_STEP_COUNT_DELTA,
         DataType.AGGREGATE_STEP_COUNT_DELTA)
        .aggregate(DataType.TYPE_HEART_RATE_BPM,
         DataType.AGGREGATE_HEART_RATE_SUMMARY)
        .aggregate(DataType.TYPE_CALORIES_EXPENDED,
         DataType.AGGREGATE_CALORIES_EXPENDED)
        .aggregate(DataType.TYPE_ACTIVITY_SEGMENT,
         DataType.AGGREGATE_ACTIVITY_SUMMARY)
        .bucketByTime(5, TimeUnit.MINUTES)
        .setTimeRange(startTime, endTime, TimeUnit.MILLISECONDS)
        .build();

        return readRequest;
}
```

The *DataType.TYPE* needs to be aggregated into *DataType.AGGREGATE* in order to obtain the data correctly. A *DataReadRequest* returns a *DataSet* in which *DataPoints* are collected. The *DataPoints* gathered have the following information referring to the time bucket defined:

- *DataType.AGGREGATE_STEP_COUNT_DELTA*: steps given (int-count).
- *DataType.AGGREGATE_HEART_RATE_SUMMARY*:
  - average (float-bpm).
  - min (float-bpm).
  - max (float-bpm).
- *DataType.AGGREGATE_CALORIES _EXPENDED*: calories expended (float - kcal).
- *DataType.AGGREGATE_ACTIVITY_SUMMARY*:
  - activity detected (int-enums).
  - duration (int-ms)

– num_segments (int-count)[1]

First of all, the method used for querying the data with the History API was *AsyncTask*, but this was rather a rough method since it required manual activation, so the procedure was finally implemented as a ***Service***. The class *QueryService* handling it *extends* its properties from *IntentService*. It sets an exact alarm with *ServiceAlarm* that launches the program after the time interval specified. The most important part of the code for activating the service it is the following:

```
public static void setServiceAlarm(Context context, boolean isOn) {
        Intent intent = QueryService.newIntent(context);
        PendingIntent pendingIntent = PendingIntent
        .getService(context, 0, intent, 0);

        AlarmManager alarmManager = (AlarmManager) context
        .getSystemService(Context.ALARM_SERVICE);

        if (isOn) {
            alarmManager.setRepeating(AlarmManager.ELAPSED_REALTIME,
                    SystemClock.elapsedRealtime(),
                    AlarmManager.INTERVAL_HOUR,
                    pendingIntent );
        } else {
            alarmManager.cancel(pendingIntent);
            pendingIntent.cancel();
        }
    }
```

The *AlarmManager* sets the repeating interval for launching the intent in which the query is defined. Note that it is set with the method *setRepeating* instead of *setInexactRepeating* for precise intervals of repetition, so it queries in perfectly scheduled time buckets of one hour.

With this distributed scheduling there is no perceptible drain of the smartphone's performance. The total Time of Execution (TE) of one hour query is:

$$TE = (3423.3 \pm 25.1)ms$$

Theory of errors has been applied to the sample, making 15 samples enough to deliver a significant result (Figure 4.7).

SQLite Storage

For prototype purpose and due to the good implementation of local SQLite databases within the Android framework, it has been selected as the database manager over any remote MySQL or Oracle implementation.

[1]Unused

One of the major problems dealing with SQLite had to do with how the Google Fit API treats the data. In spite of defining a time-bucket size for the data query (5 minutes), there are always some datapoints that do not respect that sampling time, it is rather a non-strict bucket-time definition. Moreover, Google Fit API only provides one datapoint at a time, say for example HR monitoring. This forces to collect each of the four raw *DataTypes* in a specific way. The data always comes with its own *endTime* and *startTime*, however, it is highly unlikely that those timestamps would happen to match among the different *DataTypes*. To solve that and to avoid multiple databases, each *DataType* collected is allocated in one row when received whilst the rest of colums, not available in the datapoint received, and its inferred values are set to -1 to point out that that row does not match with the data in that column (Figure 4.8).

At the end of the process, a purge is necessary to erase a low random number of blank datapoints with timestamps *startTime* and *endTime* equal to 0 and null data.

The databases are defined exactly with the same parameters than the detailed in the object description as in Figure 4.6:

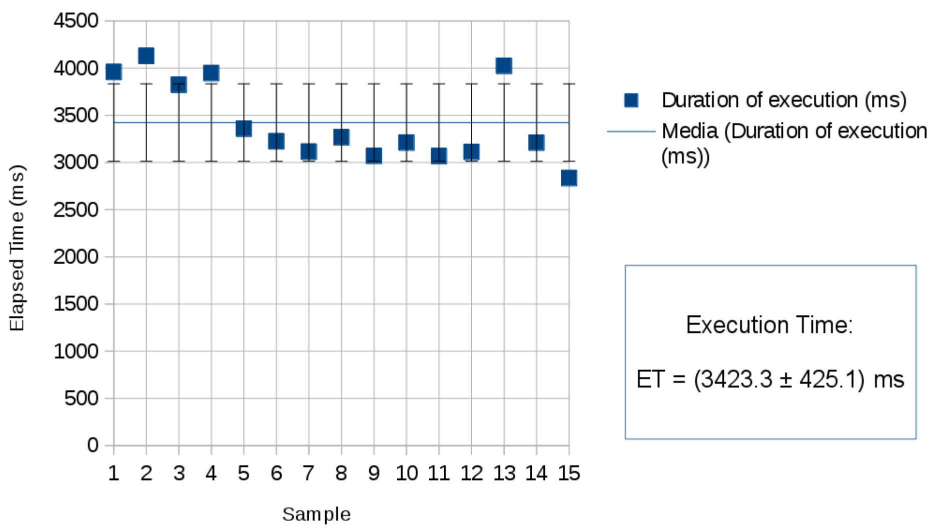


Figure 4.7: One-hour-query execution time in OncoHealth.

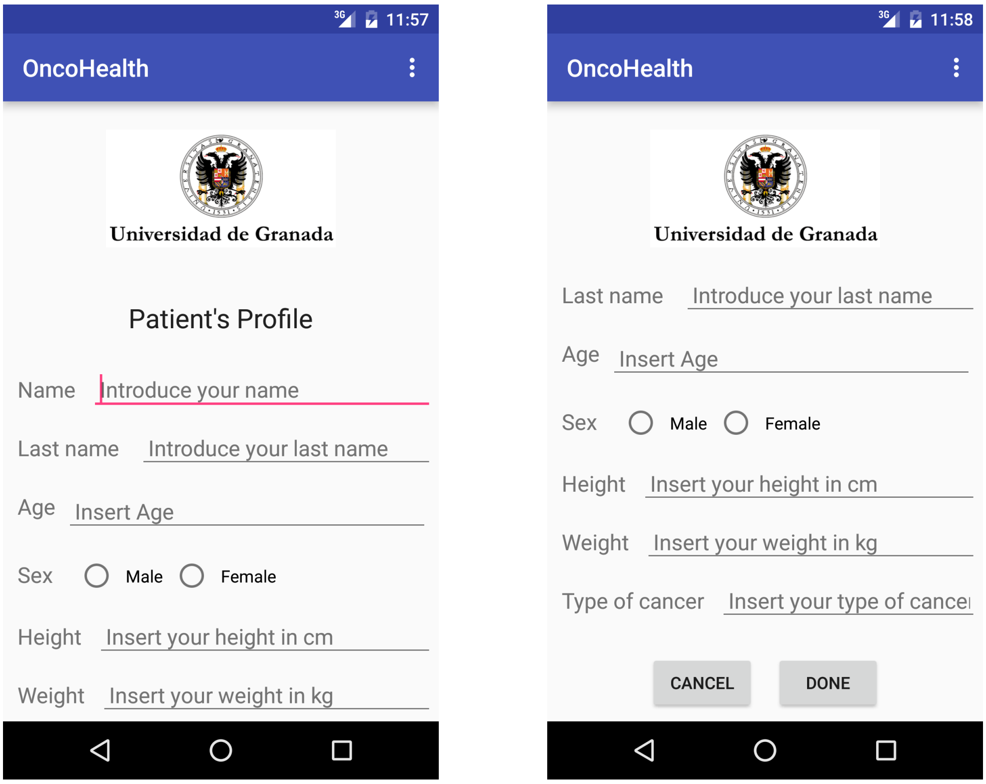
	_id	date	startTime	endTime	hrMean	hrMax	hrMin	intensityMean	intensityMax	intensityMin	activity	mets	metsIpaq	stepsDelta
	Fi...	Filter	Filter	Filter	Filter	Filter	Filter	Filter	Filter	Filter	Filter	Filter	Filter	Filter
1	1	16/05/2016 16:30:00	1463408...	14634090...	67.0	69.0	65.0	5.511811...	7.086614...	3.937007...	-1	-1.0	-1.0	-1
2	1	16/05/2016 16:31:20	1463408...	14634090...	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1	3.892608...	-1.0	-1
3	1	16/05/2016 16:31:20	1463408...	14634090...	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	3	-1.0	0.0	-1
4	1	16/05/2016 16:35:00	1463409...	14634093...	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1	-1.0	-1.0	18
5	1	16/05/2016 16:36:00	1463409...	14634093...	65.0	75.0	59.0	3.937007...	11.81102...	0.0	-1	-1.0	-1.0	-1
6	1	16/05/2016 16:36:20	1463409...	14634093...	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1	3.892608...	-1.0	-1
7	1	16/05/2016 16:36:20	1463409...	14634093...	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	3	-1.0	0.0	-1
8	1	16/05/2016 16:40:00	1463409...	14634096...	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1	-1.0	-1.0	19
9	1	16/05/2016 16:40:00	1463409...	14634096...	61.0	63.0	59.0	0.787401...	2.362204...	0.0	-1	-1.0	-1.0	-1
10	1	16/05/2016 16:41:20	1463409...	14634096...	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1	3.892608...	-1.0	-1
11	1	16/05/2016 16:41:20	1463409...	14634096...	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	3	-1.0	0.0	-1
12	1	16/05/2016 16:46:00	1463409...	14634099...	64.0	66.0	61.0	3.149606...	4.724409...	0.787401...	-1	-1.0	-1.0	-1
13	1	16/05/2016 16:46:20	1463409...	14634099...	-1.0	-1.0	-1.0	-1.0	-1.0	-1.0	-1	3.892608...	-1.0	-1

Figure 4.8: SmartBand's Database View.

- **Patient.db**: for identification purposes.
  - _id (History Number, UUID): since it is oriented to medical application, this value would relate the patient's information to the data collected in SmartBandData.db
  - Name (String)
  - Last Name (String)
  - Sex (String)
  - Age (int): in years.
  - Weight (int): in kg.
  - Body Surface (double): useful for further clinical studies. It is calculated according to the DuBois and DuBois formula [1, 2].
  - Type of cancer (String): useful for further studies.
- **SmartBandData.db**
  - _id (History Number, UUID): for identification of SmartBandData with its owner.
  - Date (String): easy display.
  - StartTime (long): UNIX time, ms.
  - EndTime (long): UNIX time, ms.
  - HR Mean (float): it is the used in algorithms depending on HR monitoring.
  - HR Max (float): only available when continuous HR monitoring activated.
  - HR Min (float): only available when continuous HR monitoring activated.
  - Intensity Mean (float): intensity calculated according to the Karvonen Formula with HR Mean [3].
  - Intensity Max (float): intensity calculated according to the Karvonen Formula with HR Max.
  - Intensity Min (float): intensity calculated according to the Karvonen Formula with HR Min.
  - Activity detected (int).
  - METs Google: conversion of Calories Expended detected according to Compendium of Physical Activities [4].
  - METs IPAQ: estimation of METs according to the intensity detected and IPAQ criteria [5].
  - Steps Delta: number of steps given in the amount of time requested.

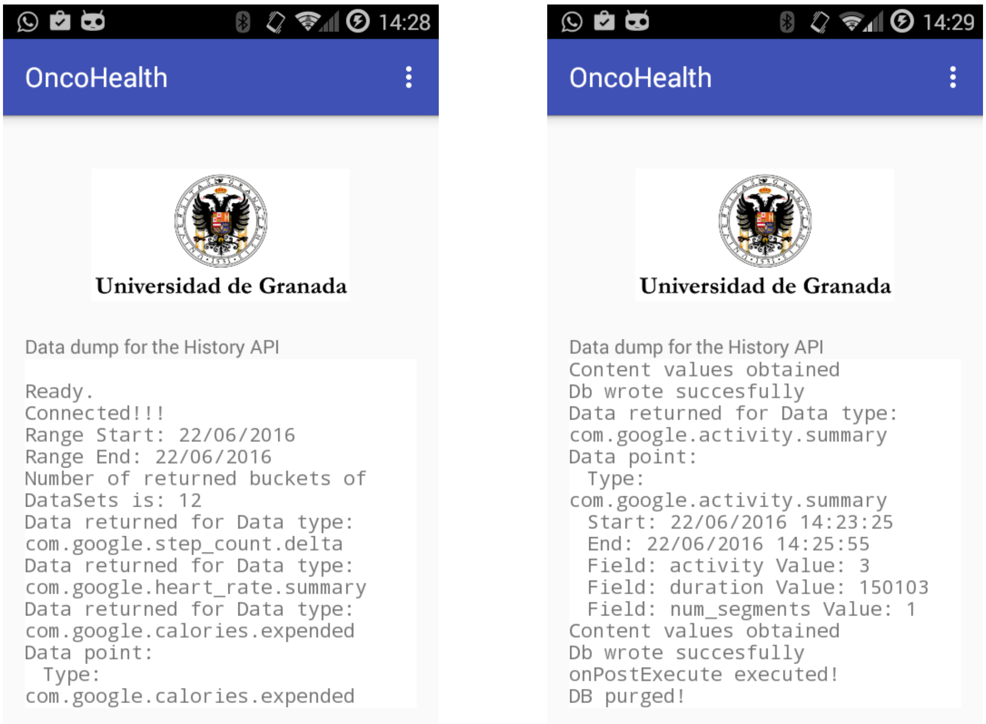
Screenshots

Some screenshots of the app can be seen in this subsection. In Figure 4.9b the interface for introducing patient's information is displayed. It only appears on the first time for associating the data collected to that user. In Figure 4.10 a log of the querying process, enabled only for debugging, is displayed.



(a) (b)

Figure 4.9: Figures of OncoHealth patient's sign up form in a ScrollView (a) top and (b) bottom
.



(a) (b)

Figure 4.10: Figures of OncoHealth query for 1 hour, (a) connection and (b) end.

4.2 Data Gathering and Processing

For the whole implementation of the algorithms an 18 days-long database has been used. I have served as tester for the biomonitoring, thus finding it easier to check on the data gathered and its accuracy.

4.2.1 IPAQ Inferring

As an alternative to the self-reported IPAQ, the following algorithm is proposed for automatic evaluation. It is built upon the algorithm depicted in the IPAQ evaluation with data obtained from continuous biomonitoring [5]. It consists of:

1. **Database query**. The following data is queried:

   - *Activity intensity* based on HR and Karvonen Formula.
   - METs for IPAQ explained later in subsubsection MET for IPAQ.

2. **Frequency adaptation**. Since the frequency of the *Activity intensity* is higher than the HR monitoring, a frequency adaptation is necessary in order to compare data. The algorithm is explained in depth in subsection Algorithm Flowcharts, page 71, Figure 4.17.

3. **Daily detection**. A day range needs to be set. Results can be seen in Figure 4.11, and an in-depth explanation in subsection Algorithm Flowcharts, page 71, Figure 4.18.

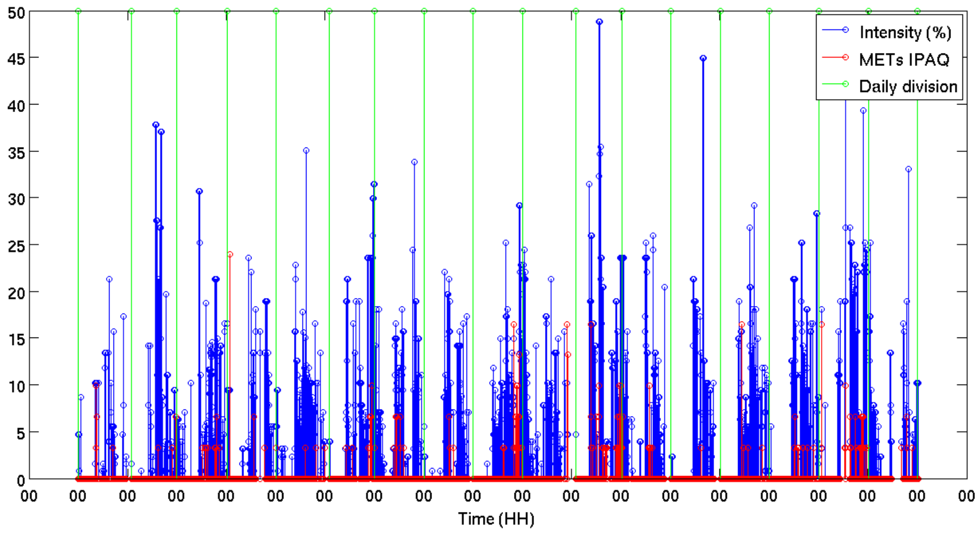


Figure 4.11: Daily detection for 18 days long database.

4. ***Activity intensity* and *METs for IPAQ* bucketing day by day**. The raw data gets organized in buckets of one day length. Both variables are composed by three different labels depending on the nature of the physical activity performed: *light*, *moderate* and *intense*.

5. ***Activity intensity* and *METs for IPAQ* sum up week by week**. Segmentation in week buckets is applied to the whole data. For each week detected, the IPAQ algorithm is evaluated:

   - *Category IPAQ 1: Low.* The lowest level of physical activity. Those individuals who not meet criteria for categories 2 or 3 are considered low/inactive.
   - *Category IPAQ 2: Moderate.* Any one of the following 3 criteria:
     - 3 or more days of vigorous activity of at least 20 minutes per day.
     - 5 or more days of moderate-intensity activity or walking of at least 30 minutes per day.
     - 5 or more days of any combination of walking, moderate-intensity or vigorous intensity activities achieving a minimum of at least 600 MET-min/week.
   - *Category IPAQ 3: High.* Any one of the following 2 criteria:
     - Vigorous-intensity activity on at least 3 days and accumulating at least 1500 MET-minutes/ week.
     - 7 or more days of any combination of walking, moderate-intensity or vigorous intensity activities achieving a minimum of at least 3000 MET-minutes/week.

MET for IPAQ

Before we enter to explain the IPAQ inferring, it is important to note how the physical activity in METs have been estimated. Since it is primarily focused in IPAQ inferring, it will specifically be counted when physical activity is detected.

One of the problems that Google Calories Expenditure presents is that it considers always the RMR, so it points out calorie expenditure even when total resting is detected. The IPAQ does not take into account this kind of activity, therefore, to filter this, the IPAQ MET expenditure has been calculated only when an *activity* different from *EXCEPTION*, *IN_VEHICLE*, *STILL*, *DEEP_SLEEP*, *LIGHT_SLEEP*, *REM_SLEEP* and *AWAKE_SLEEP* is detected. All those activities automatically have set a MET value of zero, which means no physical activity at all. The *activities* that are enabled to calculate the MET expediture are *CYCLING*, *ON_FOOT*, *WALKING* and *RUNNING*, since most of physical activities imply on foot movement in different grades of intensity. The activity *CYCLING* count with its own MET expenditure since it is automatically detected, always according to the Compendium of Physical Activity [4].

The MET expenditure is calculated following these criteria [5]. The intensity is inferred directly from HR according to Karvonen's Formula [3]:

- *Light* activity intensity. $MET = 3.3 \cdot duration\ (MET \cdot min)$
- *Moderate* activity intensity. $MET = 4 \cdot duration\ (MET \cdot min)$
- *Vigorous* activity intensity. $MET = 8 \cdot duration\ (MET \cdot min)$
- *Cycling* activity intensity. $MET = 6 \cdot duration\ (MET \cdot min)$

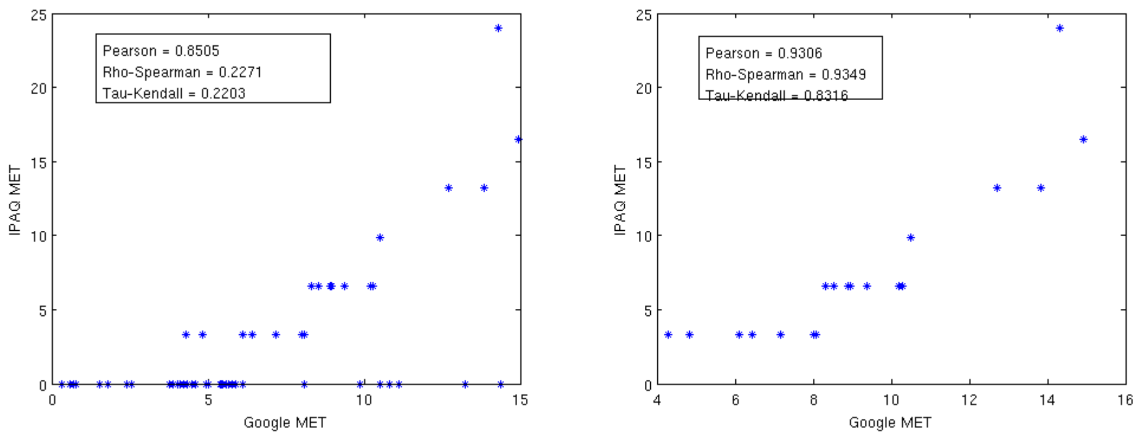
A comparison of the METs inferred with IPAQ rules and with the Google Calorie Expenditure, transformed to METs, for a database along 18 days long, can be seen in Figure 4.12. In Figure 4.12a a good Pearson correlation coefficient of 0.8505 is obtained, but because of the outliers the Spearman and Kendall scores point out a rather low correlation. Nevertheless, if the outliers are taken out of the comparison (just 49 points over a total of 3385, points where Google detected minor activity whilst the IPAQ remained to zero), it can be seen in Figure 4.1b how very good scoring is obtained for all the correlation coefficients, finding a 0.9306 for Pearson, 0.9349 for Spearman and a 0.8316 for Kendall.

These results **validate** the use of this IPAQ algorithm for exclusive physical activity detection in METs. The time considered for the IPAQ activities is strictly the one attached to physical activity, that is, the time in which METs evaluated are higher than zero. The resulting time recorded along the 18 days can be seen in Figure 4.13. In the data presented the following activities can be highlighted to validate the algorithm:

1. Two one-hour-and-a-half-long paddle matches in days 10 and 17. The breaks and starting and ending times are correctly not detected as physical activity.

2. An hour-and-a-quarter-long music concert performed in day 12. The duration of the activity shown is quite accurately the time I was on stage.

The rest of the time a rather sedentary or low level activity performed is found. This leads to an **IPAQ scoring of 1 (LOW) for each of the two weeks detected**, which seems appropriate according to the sporadic exercise done.



(a) (b)

Figure 4.12: METs calculation comparison between Google estimation and IPAQ algorithm (a) with all the data and (b) without outliers.

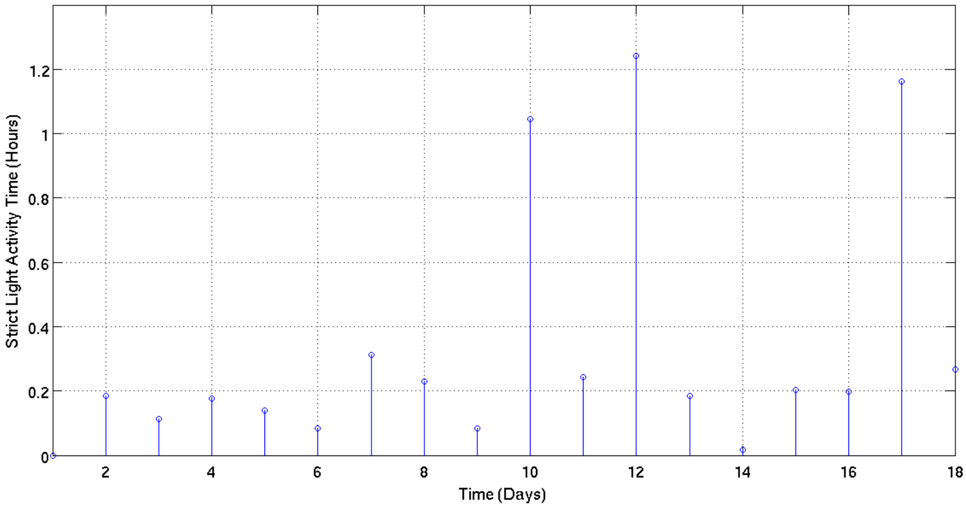


Figure 4.13: Strict Light Activity Detection

4.2.2 ECOG and KPS Inferring

Since no precedent for automatic ECOG and KPS inferring algorithms was found in the extent review of the State of the Art (page 14), there has been some liberty when defining the conditions for classifying the patients, but always according to the references cited along the descriptions.

In this subsection the ECOG and KPS algorithm is presented. Unlike the IPAQ inferring, the PS measure does not focus strictly on the intensity of physical activity, it remarks on the tendency and continuity of the exercise done, even if it is performed at a very low level of intensity. Thus, a more flexible duration of *light*, *moderate* and *vigorous* activities is necessary to measure the activities beyond absolute rest. Here it is reminded that most of cancer patients tend to have long resting periods of time in bed or chair due to the physical weakness and fatigue acquired in the treatment.

At first, the time considered for *light* activity was strictly all the gathered with intensity in the interval $[0, 50)\%$ [6]. Nevertheless, this was almost all the time available in which any activity was detected, so, levelling up the *light* intensity standards was tried. The algorithm would now take into account the data in the interval $(X, 50)\%$ where $X = \{0, 1, 2, 3, 4, 5\}\%$.

With this, the algorithm is trying to offer slightly different perspectives, more or less restrictive, to the same measure of PS. This is specially important when the conditions for calculating come from the very ambiguous classification guide that ECOG and KPS supply. The only numeric condition they contain is to be out of bed more than 50% of the time available or not, which is found in the gap between 2 and 3 ECOG. This gap equals the one between 50 and 60 KPS [7]. Taking this into account, another objective measure was needed: the steps count. This extra measure will help to evaluate the level of activity according to the total steps done day by day [8]. The following points conform the algorithm:

1. **Database query**. The following data is queried:

    - *Activity Detected* (AD).

- *Activity Intensity* based on HR.
- *Steps delta* counted in 5-min-long time buckets.

2. **Frequency adaptation**. Since the frequency of the AD is higher than the HR monitoring, a frequency adaptation is necessary to compare *Activity intensity* with AD. The algorithm in subsection Algorithm Flowcharts, page 71, Figure 4.17 is applied to these variables.

3. **Daily detection**. Algorithm in subsection Algorithm Flowcharts, page 71, Figure 4.18 is applied to the following data:

   - *Activity intensity* and AD after frequency adaptation.
   - *Steps Delta*.

4. **Day-by-day Bucketing**. The raw data gets organized in buckets of one day length. It is divided in:

   - *Steps Delta*.
   - Sleep Tracking: *Light*, *deep*, *REM* and *awake* sleep. The whole sum is equal to the total sleeping time of each day.
   - *Activity intensity* with multiple division depending on the intervals defined for *light* intensity: $(X, 50)\%$ where $X = \{0, 1, 2, 3, 4, 5\}\%$.

5. **Calculation of the daily proportion of AD time**. It is applied to each of the divisions defined for *Light* activity, plus the *moderate* and *high* activity. The sleeping time detected is taken out of the proportion of every day. In Figure 4.14 the results are presented.

6. **Weekly segmentation**. ECOG and KPS rule base (Table 4.1) applied to the weekly segmented data.

The setting of margins for the light activity level detection is intended to serve as an indicator for the oncologist analysing the data. In Figures 4.15 and 4.16 the results are shown. **The first week scores at 0% level with 90 KPS and 1 ECOG, higher than the rest of levels with 70 KPS and 2 ECOG; the second week strikes with 70 KPS and 2 ECOG for all the possibilities**. The "optimistic" filter of 0% margin for the *light* activity measure helps this differing, even if there is a higher exercise amount in the second week. That is because it is the prevalence of tendencies and the long term activity what really scores in the KPS and ECOG inferring. The paddle match and the concert may have impact on the IPAQ, but not enough to raise it to 2.

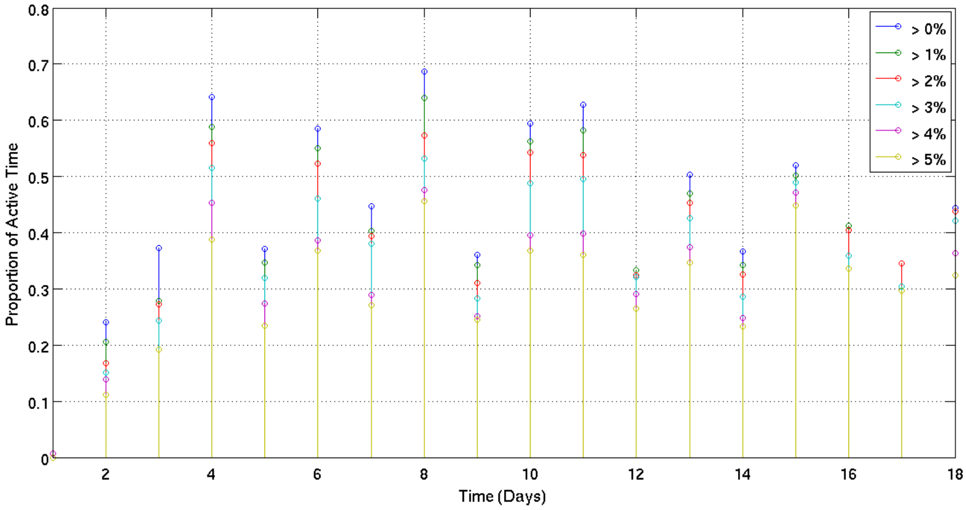


Figure 4.14: Daily proportion of user's Active Time

RULE BASE				
IPAQ	Proportion	Steps	ECOG	KPS
3	>=0.5	5	0	100
		4	0	100
		3	0	100
		2	0	100
		1	0	100
	<0.5	5	0	100
		4	0	100
		3	0	100
		2	0	90
		1	1	90
2	>=0.5	5	0	100
		4	0	100
		3	0	100
		2	1	90
		1	1	80
	<0.5	5	0	100
		4	0	100
		3	1	90
		2	2	80
		1	2	70
1	>=0.5	5	1	90
		4	1	90
		3	2	80
		2	2	70
		1	2	60
	<0.5	5	2	70
		4	2	70
		3	3	60
		2	3	50
		1	4	40

(a)

LEGEND		
Steps Count	Intensity	
sc > 12.500	5	Very High
10.000< sc <12.500	4	High
7.500< sc <10.000	3	Normal
5.000< sc <7.500	2	Low
Sc <5.000	1	Very Low

IPAQ	Intensity
3	High
2	Moderate
1	Low

Proportion	Legend
>=0.5	More than 50% active time out of bed
<0.5	Less than 50% active time out of bed

ECOG	Legend
0	Best (Asymptomathic)
1	...
2	
3	
4	
5	Worst (Exitus)

KPS	Legend
100	Best (Asymptomathic)
90	...
...	
...	
10	
0	Worst (Exitus)

(b)

Table 4.1: (a) Rule base for ECOG and KPS inferring with (b) legend.

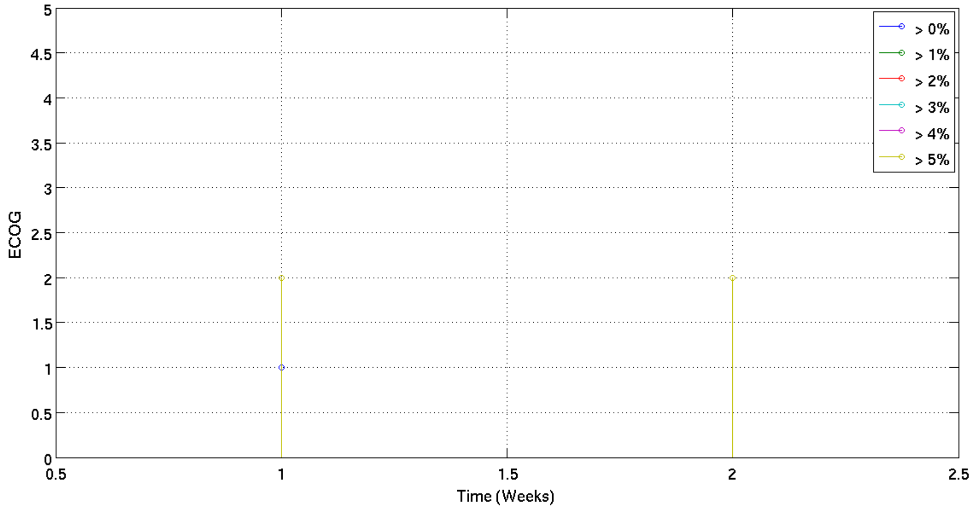


Figure 4.15: ECOG performance along two weeks with IPAQ = 1

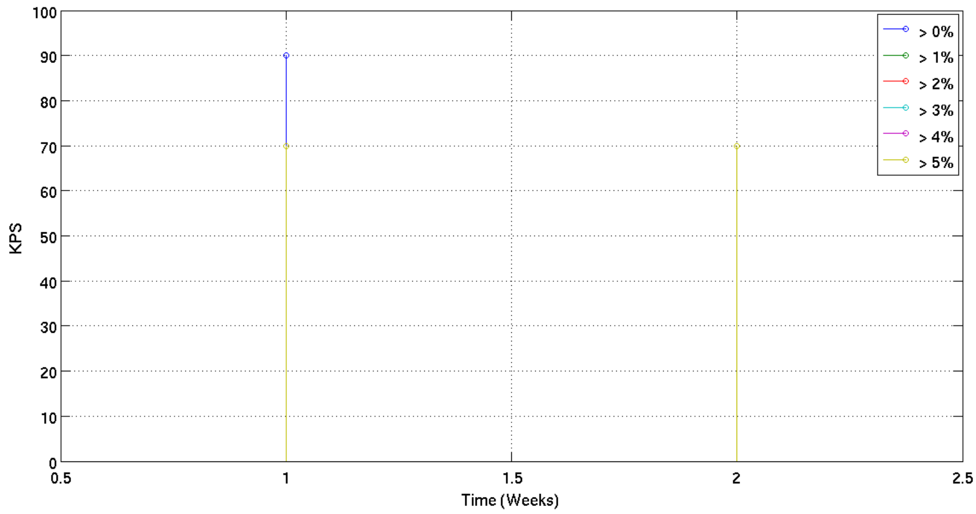


Figure 4.16: KPS performance along two weeks with IPAQ = 1

4.2.3 Algorithm Flowcharts

Frequency Adaptation Algorithm

Different and irregular sampling frequencies demand a frequency adaptation in order to compare among the different data gathered and inferred.

For the IPAQ inferring, the algorithm (Figure 4.17) mainly consists of introducing the data with lower sampling frequency, *activity intensity*, also called *HR intensity*, into the same matrix where *METs for IPAQ* are. It assumes that those gaps in the sampling are because no significant change was found, so to fill that blank data, the immediate previous *activity intensity* is saved.

For the ECOG the same algorithm is applied to *activity detected* (higher sampling frequency) and *activity intensity* (lower sampling frequency).

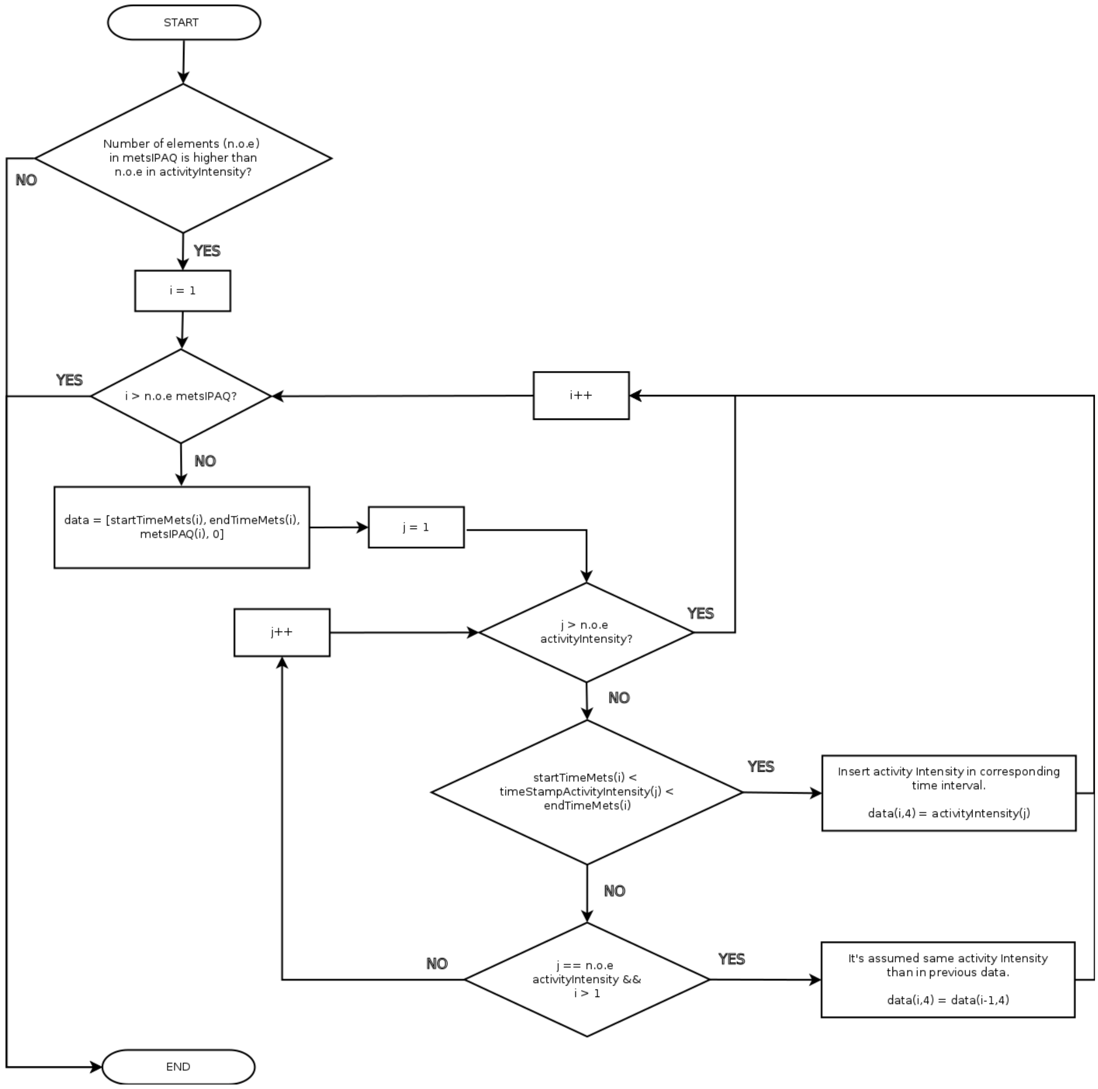


Figure 4.17: Frequency adaptation algorithm

Daily Detection Algorithm

For both IPAQ and ECOG-KPS inferring this algorithm (Figure 4.18) is applied to bucket the data day by day. The hour detection starts at 00:00 for each day of the month; the algorithm looks for the first data allocated with that settings. If no data is found matching the hour given then the next loop will try with the next hour (00:00 then 01:00 then 02:00 ... then 23:00). The loop is applied to each datapoint. When matching hour is detected, the loop jumps to the next day looking for the earliest hour available.

4.3 Summary

In this chapter all the results obtained with its procedures have been detailed. The architecture proposed at the end of Chapter 3 (page 46) has been propperly implemented and physical activity and PS algorithms have been developed with good results.

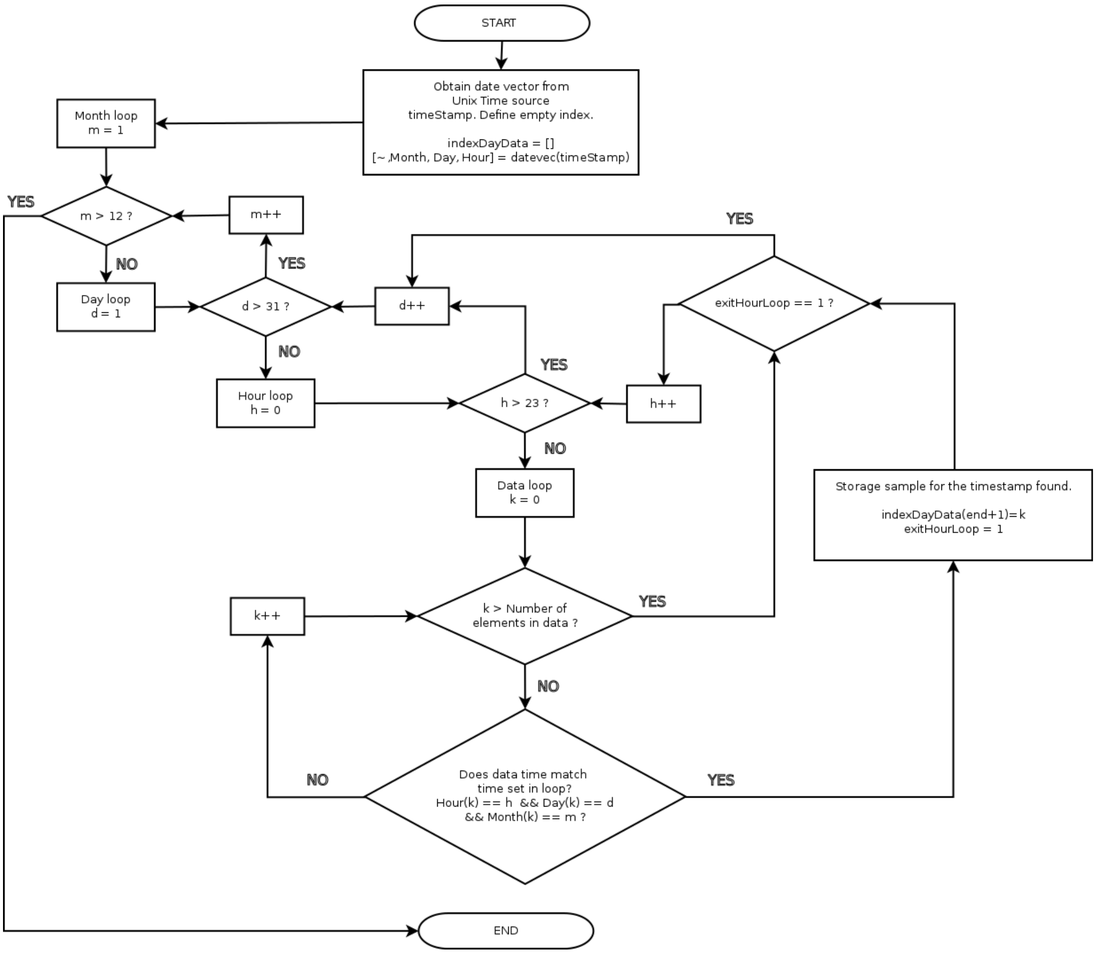


Figure 4.18: Daily detection algorithm

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[6] Target Heart Rate and Estimated Maximum Heart Rate | Physical Activity | CDC. http://www.cdc.gov/physicalactivity/basics/measuring/heartrate.htm. Online, accessed 2016-05-09.

[7] G. Buccheri, D. Ferrigno, and M. Tamburini. Karnofsky and ECOG performance status scoring in lung cancer: A prospective, longitudinal study of 536 patients from a single institution. *European Journal of Cancer*, 32(7):1135–1141, June 1996.

[8] Catrine Tudor-Locke and David R. Bassett Jr. How many steps/day are enough? *Sports medicine*, 34(1):1–8, 2004.

Chapter 5

Conclusions and Future Work

5.1 Conclusions

The recovery and evaluation of cancer patients is a major and global issue that has been clearly presented with needs for improvement. An entirely new approach to automatic PS evaluation has been proposed without any precedent known, and besides, the system makes the most of commercial devices in the wearable market. It is not only the relevance of the algorithms developed, but also the implementation with common and affordable components that almost everybody already owns like Android-based smartphones and activity trackers. Thus, from both personal and research objectives, many different goals have been successfully reached:

- A complex project involving several disciplines has been properly designed and implemented.
- An extensive study of the *State of the Art* to the very different subjects tackled along the report has been done: cancer patient's recovery, Performance Status evaluation, Physical Activity assessment, Gamification and mHealth.
- A reasonable evaluation of the necessities of the project has been done according to the wearable and portable devices market status and catalogue.
- New technologies have been addressed according to the needs and project's magnitude: Object-Oriented Programming, Android programming, Google Fit API interaction and database management with SQLite. Known tools have also been used such as MATLAB and data processing techniques.
- Gamification techniques have been studied along with the most relevant cancer patients' psychological condition and a proper design has been developed.
- New and with no precedent known PS algorithms have been developed to infer ECOG and KPS in cancer patients.
- Relevant results have been accomplished, enabling prospective publications in scientific journals.
- An adequate report has been done gathering all the work done.

It is also important to highlight the difficulties of sharing information with other specialists and the success on it in this project. As an engineer, it is not always easy to guess what are the client's needs – oncologists' needs in this case. There is usually a big gap between the client's needs and the engineer's functional requirements that has to be effectively tackled in the fluent and several conversations done. Finally, this work has provided me very valuable skills in this field as an engineer.

To sum up, I would like to point out that this work emerges from the need for a suitable and objective evaluation of cancer patients, and that it proposes a fairly new method to assist oncologists in the PS evaluation of cancer patients with ECOG and KPS scales.

5.2 Future Work

This work is intended to be just the beginning of something bigger. It has the potential to be tested directly to evaluation and validation with real patients. Furthermore, several improvements and new leads of research are opened to keep progressing. The most immediate steps to continue with are the following:

1. Apply for a patent.
2. Present the project to the Ethics Committee of the Hospital *Virgen de las Nieves, Granada* to get the permission to test the system with real patients.
3. Keep working on the gamified framework for the patients, developing a full app to interact with.
4. In the ECOG and KPS inferring a typical Rule Base for Fuzzy Logic Controllers has been defined so it could be implemented. Besides, if there is availability of enough data, even Machine Learning algorithms could be applied to infer new rules non devised on a first sight.
5. Public a scientific paper based upon this work in order to obtain the full amount of the University of Granada's Starting Grant that I am enjoying.

To conclude, I would like to express the high value of this project. It is sure something that, with enough work, may eventually contribute to the whole society. This is not only because of its direct application to cancer patient's recovery – the main motivation – but also all the advances still to come in the technologies involved within the mHealth filed that will start the transition to a new medicine paradigm.

Appendix

User's Manual: Patient

Along this manual it is going to be presented the installation and first use dialogues.

First of all, it is necessary to install any request that the wearable used may require. In this prototype, the Sony SmartBand 2 SWR12 is used, so the application "SmartBand 2 SWR12" must be installed from Google Play (Figure 5.1).

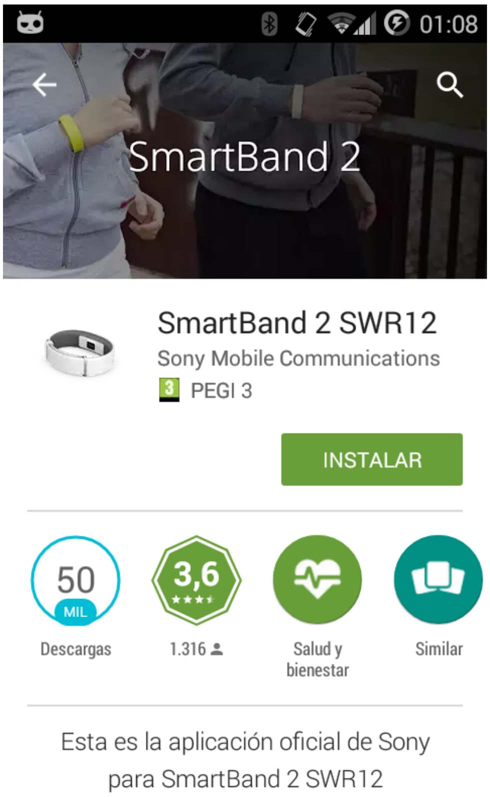
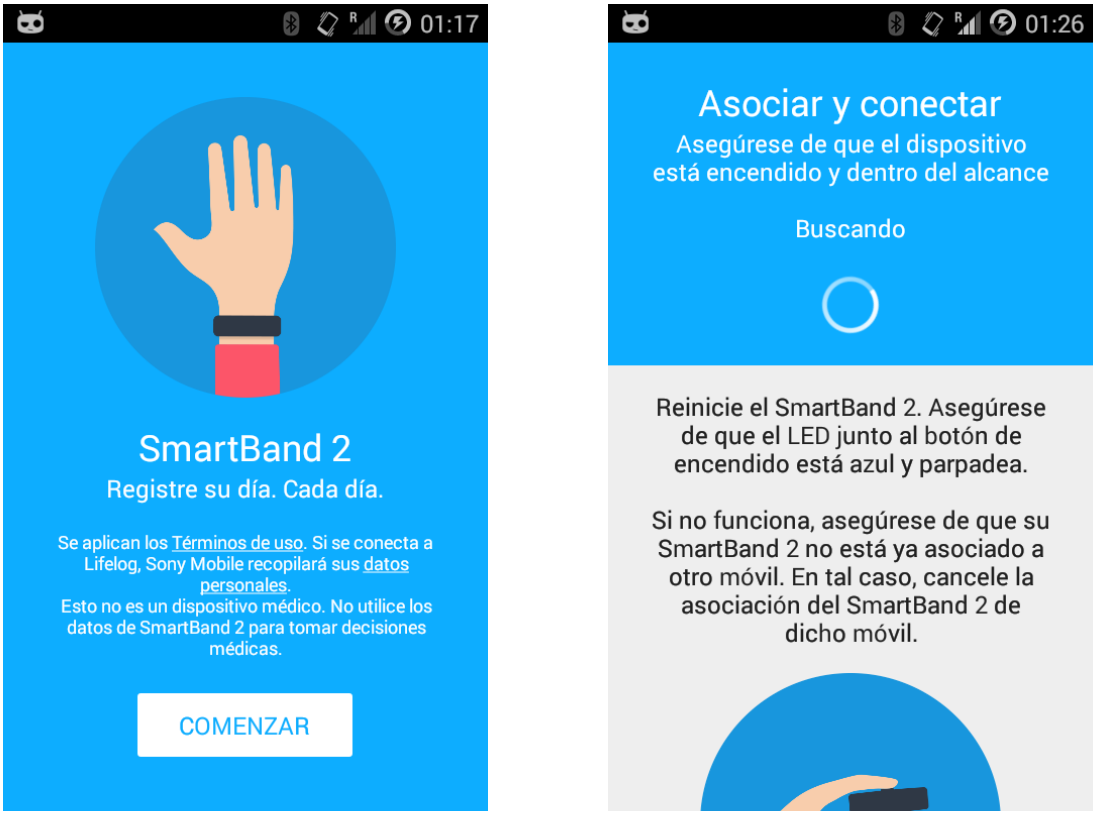


Figure 5.1: Install "SmartBand 2 SWR12" from Google Play

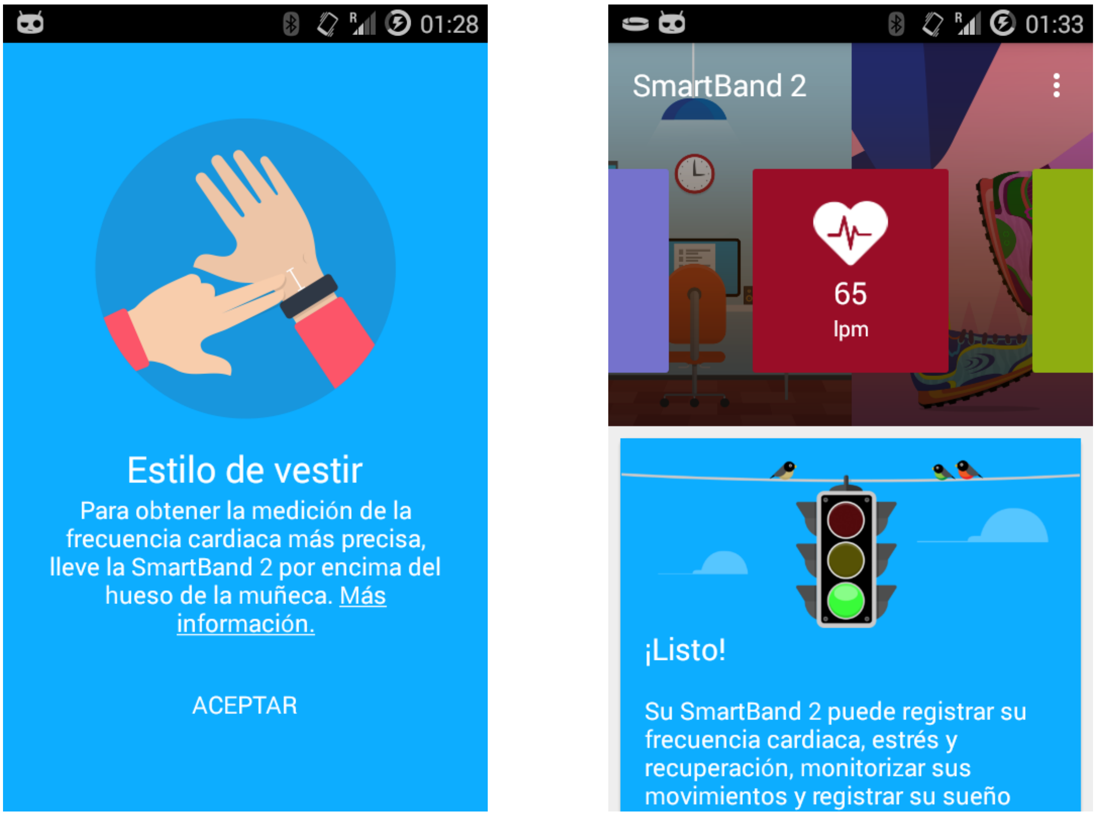
Then, the app guides the user through a first use guide to connect the SmartBand 2 (Figure 5.2). Make sure have the SmartBand2 fully charged at connection. Three blue leds should blink when connection with the smartphone is established.



(a) (b)

Figure 5.2: (a)Welcome screen and (b) SmartBand 2 connection screen.

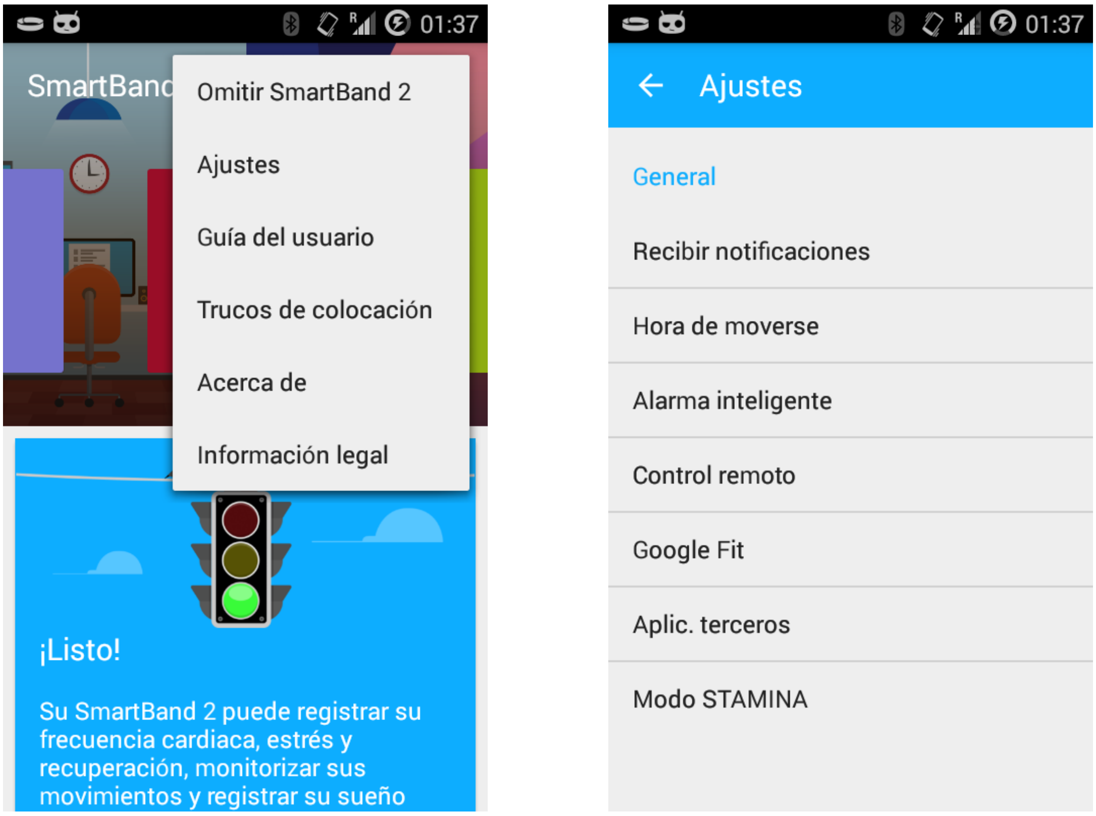
Next screen will recommend the way to wear the SmartBand 2, about 2 cm over the wrist's bone. Once accepted, the main view of the SmartBand 2 app is seen (Figure 5.3).



(a) (b)

Figure 5.3: (a)Wearing recommendations and (b) main SmartBand 2 SWR12 view.

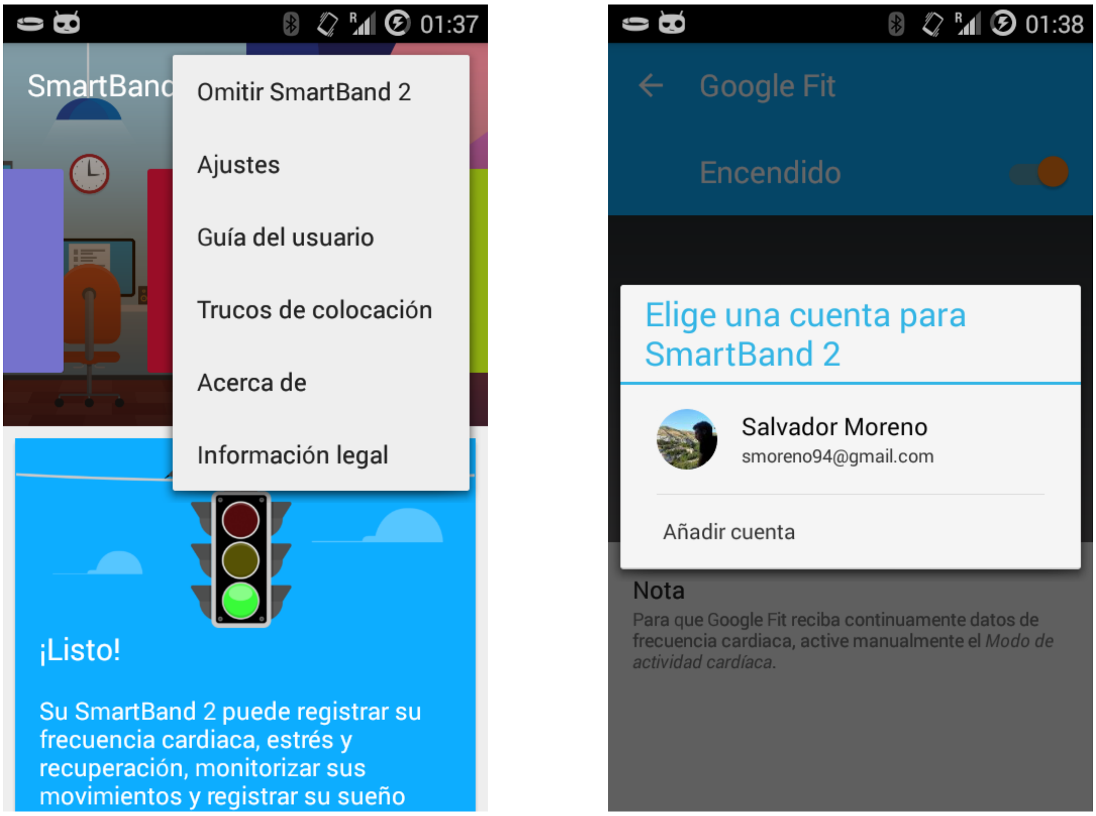
Next, it is necessary to enable the Google Fit Connexion. For this, we enter into "Settings" - "Google Fit" and turn on the the connectivity with Google Fit (Figure 5.4).



(a) (b)

Figure 5.4: (a) General menu display and (b) Settings menu.

Once enabled, you will be requested for authentication and authorization for your data to be requested by Google Fit through your Google account (Figure 5.5)

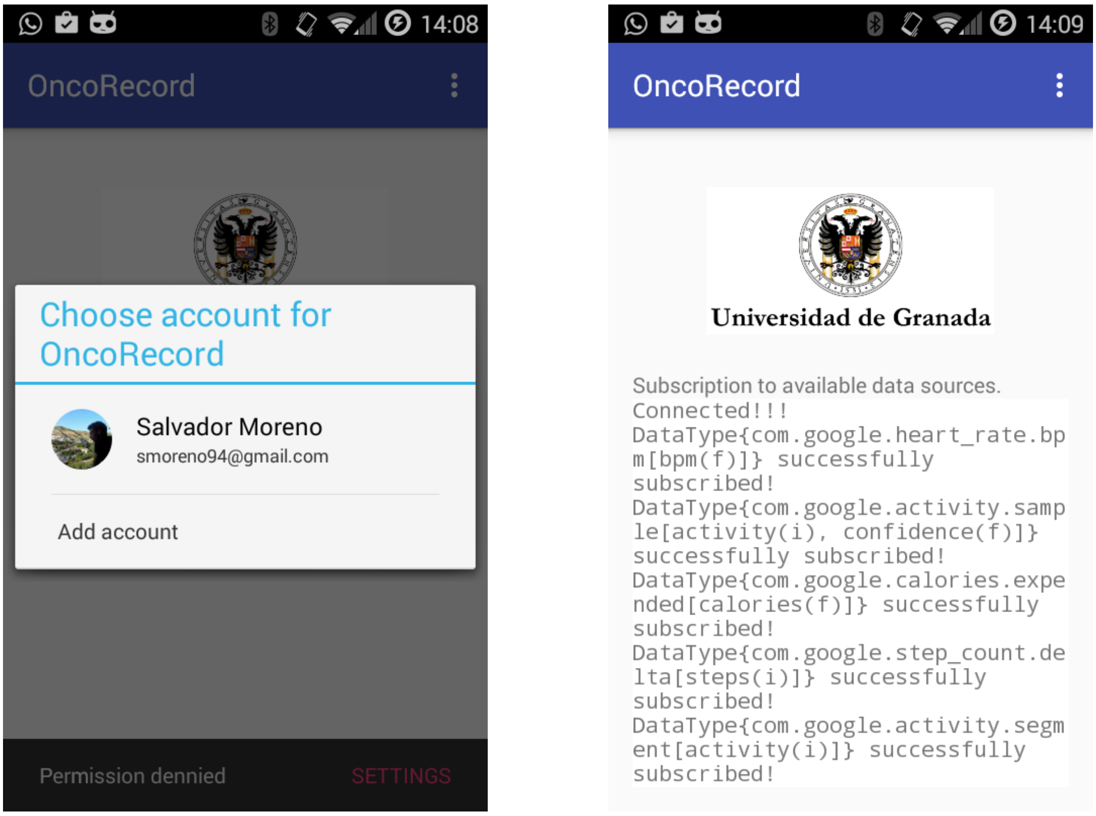


(a) (b)

Figure 5.5: (a) Google Fit connection tab enabled and (b) Google authorization request.

With all this steps done, the environment is ready to install the *OncoRecord* and *OncoHealth* apps. Both will be installed manually since there are not yet listed within the Google Play applications.

Once **OncoRecord** is installed, there will be an authorization request for data collection from Google Play. Then the listeners registered will be shown (Figure 5.6).



(a) (b)

Figure 5.6: (a) Authorization request and (b) data listeners activated.

Done this, you can proceed to the first start of **OncoHealth**. A first screen will ask for the patient details (Figure 5.7).

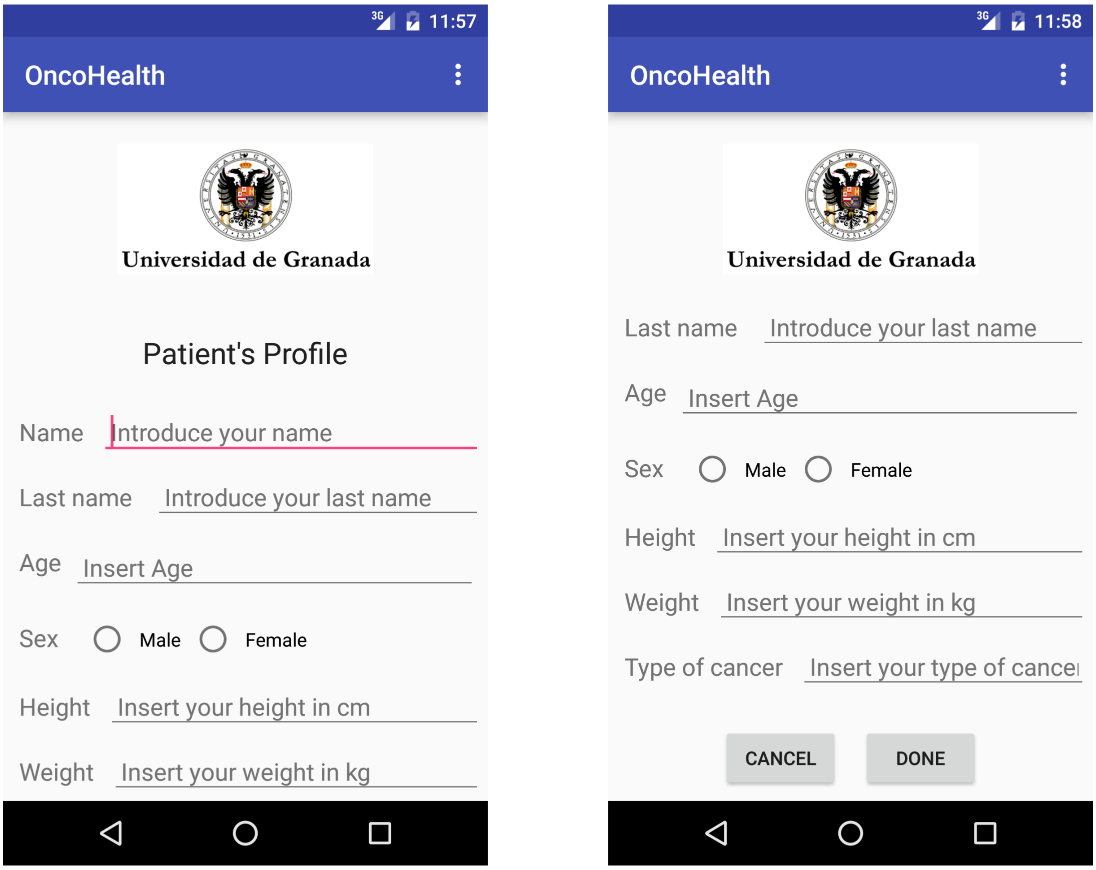


Figure 5.7: Patient's sign up screen (a) top and (b) bottom.

Finally, another authorization screen is presented. Once accepted, a test request to Google Fit is performance to finally activate the service that will gather automatically the data.

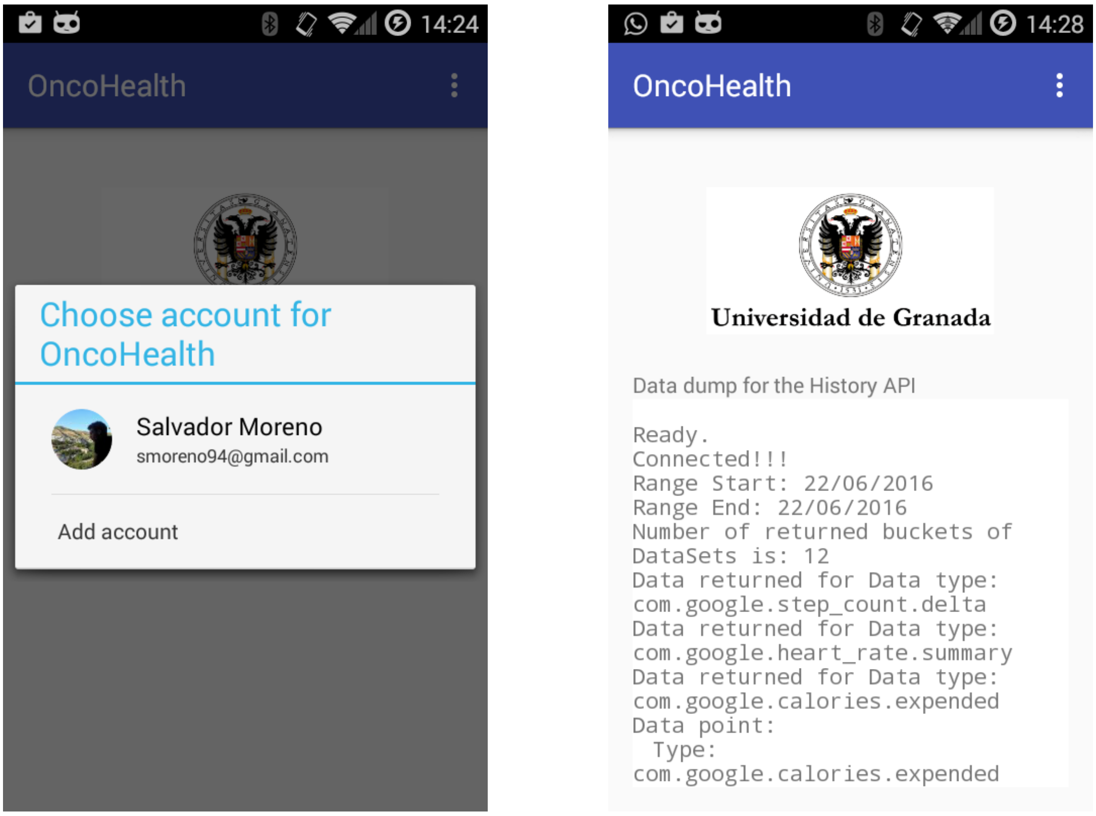


Figure 5.8: (a) Authorization request and (b) test request with service activation.

IPAQ

Short IPAQ, English Version - USA

The English version of the Short IPAQ is the original IPAQ from where all the translations are done. Some may be adapted with minor changes depending on the place of application.

INTERNATIONAL PHYSICAL ACTIVITY QUESTIONNAIRE (August 2002)

SHORT LAST 7 DAYS SELF-ADMINISTERED FORMAT

FOR USE WITH YOUNG AND MIDDLE-AGED ADULTS (15-69 years)

The International Physical Activity Questionnaires (IPAQ) comprises a set of 4 questionnaires. Long (5 activity domains asked independently) and short (4 generic items) versions for use by either telephone or self-administered methods are available. The purpose of the questionnaires is to provide common instruments that can be used to obtain internationally comparable data on health–related physical activity.

Background on IPAQ
The development of an international measure for physical activity commenced in Geneva in 1998 and was followed by extensive reliability and validity testing undertaken across 12 countries (14 sites) during 2000. The final results suggest that these measures have acceptable measurement properties for use in many settings and in different languages, and are suitable for national population-based prevalence studies of participation in physical activity.

Using IPAQ
Use of the IPAQ instruments for monitoring and research purposes is encouraged. It is recommended that no changes be made to the order or wording of the questions as this will affect the psychometric properties of the instruments.

Translation from English and Cultural Adaptation
Translation from English is supported to facilitate worldwide use of IPAQ. Information on the availability of IPAQ in different languages can be obtained at www.ipaq.ki.se. If a new translation is undertaken we highly recommend using the prescribed back translation methods available on the IPAQ website. If possible please consider making your translated version of IPAQ available to others by contributing it to the IPAQ website. Further details on translation and cultural adaptation can be downloaded from the website.

Further Developments of IPAQ
International collaboration on IPAQ is on-going and an ***International Physical Activity Prevalence Study*** is in progress. For further information see the IPAQ website.

More Information
More detailed information on the IPAQ process and the research methods used in the development of IPAQ instruments is available at www.ipaq.ki.se and Booth, M.L. (2000). *Assessment of Physical Activity: An International Perspective*. Research Quarterly for Exercise and Sport, 71 (2): s114-20. Other scientific publications and presentations on the use of IPAQ are summarized on the website.

INTERNATIONAL PHYSICAL ACTIVITY QUESTIONNAIRE

We are interested in finding out about the kinds of physical activities that people do as part of their everyday lives. The questions will ask you about the time you spent being physically active in the **last 7 days**. Please answer each question even if you do not consider yourself to be an active person. Please think about the activities you do at work, as part of your house and yard work, to get from place to place, and in your spare time for recreation, exercise or sport.

Think about all the **vigorous** activities that you did in the **last 7 days**. **Vigorous** physical activities refer to activities that take hard physical effort and make you breathe much harder than normal. Think *only* about those physical activities that you did for at least 10 minutes at a time.

1. During the **last 7 days**, on how many days did you do **vigorous** physical activities like heavy lifting, digging, aerobics, or fast bicycling?

   _____ **days per week**

   ☐ No vigorous physical activities → ***Skip to question 3***

2. How much time did you usually spend doing **vigorous** physical activities on one of those days?

   _____ **hours per day**

   _____ **minutes per day**

   ☐ Don't know/Not sure

Think about all the **moderate** activities that you did in the **last 7 days**. **Moderate** activities refer to activities that take moderate physical effort and make you breathe somewhat harder than normal. Think only about those physical activities that you did for at least 10 minutes at a time.

3. During the **last 7 days**, on how many days did you do **moderate** physical activities like carrying light loads, bicycling at a regular pace, or doubles tennis? Do not include walking.

   _____ **days per week**

   ☐ No moderate physical activities → ***Skip to question 5***

4. How much time did you usually spend doing **moderate** physical activities on one of those days?

_____ **hours per day**

_____ **minutes per day**

☐ Don't know/Not sure

Think about the time you spent **walking** in the **last 7 days**. This includes at work and at home, walking to travel from place to place, and any other walking that you have done solely for recreation, sport, exercise, or leisure.

5. During the **last 7 days**, on how many days did you **walk** for at least 10 minutes at a time?

_____ **days per week**

☐ No walking → ***Skip to question 7***

6. How much time did you usually spend **walking** on one of those days?

_____ **hours per day**

_____ **minutes per day**

☐ Don't know/Not sure

The last question is about the time you spent **sitting** on weekdays during the **last 7 days**. Include time spent at work, at home, while doing course work and during leisure time. This may include time spent sitting at a desk, visiting friends, reading, or sitting or lying down to watch television.

7. During the **last 7 days**, how much time did you spend **sitting** on a **week day**?

_____ **hours per day**

_____ **minutes per day**

☐ Don't know/Not sure

This is the end of the questionnaire, thank you for participating.

Short IPAQ, Spanish Version - Spain, Junta de Andalucia

This is the official Short IPAQ version used within the Andalusian hospitals (Spain).

VERSIÓN PARA LOS USUARIOS/AS DE LA EMPRESA

CUESTIONARIO INTERNACIONAL DE ACTIVIDAD FÍSICA (IPAQ)

Nos interesa conocer el tipo de actividad física que usted realiza en su vida cotidiana. Las preguntas se referirán al tiempo que destinó a estar activo/a en los últimos 7 días. Le informamos que este cuestionario es totalmente anónimo.

Muchas gracias por su colaboración

1.- Durante los últimos 7 días, ¿en cuántos realizo actividades físicas intensas tales como levantar pesos pesados, cavar, ejercicios hacer aeróbicos o andar rápido en bicicleta?	
Días por semana (indique el número)	
Ninguna actividad física intensa (pase a la pregunta 3)	☐
2.- Habitualmente, ¿cuánto tiempo en total dedicó a una actividad física intensa en uno de esos días?	
Indique cuántas horas por día	
Indique cuántos minutos por día	
No sabe/no está seguro	☐
3- Durante los últimos 7 días, ¿en cuántos días hizo actividades físicas moderadas tales como transportar pesos livianos, o andar en bicicleta a velocidad regular? No incluya caminar	
Días por semana (indicar el número)	
Ninguna actividad física moderada (pase a la pregunta 5)	☐
4.- Habitualmente, ¿cuánto tiempo en total dedicó a una actividad física moderada en uno de esos días?	
Indique cuántas horas por día	
Indique cuántos minutos por día	
No sabe/no está seguro	☐
5.- Durante los últimos 7 días, ¿en cuántos días caminó por lo menos 10 minutos seguidos?	
Días por semana (indique el número)	
Ninguna caminata (pase a la pregunta 7)	☐
6.- Habitualmente, ¿cuánto tiempo en total dedicó a caminar en uno de esos días?	
Indique cuántas horas por día	
Indique cuántos minutos por día	
No sabe/no está seguro	☐
7.- Durante los últimos 7 días, ¿cuánto tiempo pasó sentado durante un día hábil?	
Indique cuántas horas por día	
Indique cuántos minutos por día	
No sabe/no está seguro	☐

VALOR DEL TEST:

1. Caminatas: 3'3 MET* x minutos de caminata x días por semana (Ej. 3'3 x 30 minutos x 5 días = 495 MET)
2. Actividad Física Moderada: 4 MET* X minutos x días por semana
3. Actividad Física Vigorosa: 8 MET* X minutos x días por semana

A continuación sume los tres valores obtenidos:

Total = caminata + actividad física moderada + actividad física vigorosa

CRITERIOS DE CLASIFICACIÓN:

- Actividad Física Moderada:
  1. 3 o más días de actividad física vigorosa por lo menos 20 minutos por día.
  2. 5 o más días de actividad física moderada y/o caminata al menos 30 minutos por día.
  3. 5 o más días de cualquiera de las combinaciones de ca minata, actividad física moderada o vigorosa logrando como mínimo un total de 600 MET*.
- Actividad Física Vigorosa:
  1. Actividad Física Vigorosa por lo menos 3 días por semana logrando un total de al menos 1500 MET*.
  2. 7 días de cualquier combinación de caminata, con actividad física moderada y/o actividad física vigorosa, logrando un total de al menos 3000 MET*.

*** Unidad de medida del test.**

RESULTADO: NIVEL DE ACTIVIDAD (señale el que proceda)	
NIVEL ALTO	☐
NIVEL MODERADO	☐
NIVEL BAJO O INACTIVO	☐

Para finalizar, le vamos a pedir que registre algunos datos de interés estadístico:

SEXO: Hombre ☐ Mujer ☐

EDAD: ______________________

EMPRESA/INSTITUCIÓN: ______________________

CENTRO DE TRABAJO: ______________________

POBLACIÓN: ______________________

PROFESIÓN: ______________________

CATEGORÍA PROFESIONAL: ______________________

DEPARTAMENTO EN EL QUE TRABAJA: ______________________

Los resultados se tratarán de forma global y se mantendrá el anonimato en las publicaciones que puedan derivarse de este cuestionario.

La transmisión de datos se hará con las medidas de seguridad adecuadas en cumplimiento de la Ley Orgánica 15/1599 de Protección de Datos de Carácter Personal y el Real Decreto 994/99.

Google Fit's DataTypes

Here are listed the DataTypes for instantaneous and aggregated DataPoints.

Data types for instantaneous readings

These data types are defined as public fields of the `DataType` class. Their field names start with the `TYPE_` prefix.

Data Type Name	Description	Permissio n	Fields (Format—Unit)
com.	Instantaneous sample of the current activity.	Activity	activity (int—enum) confidence (float—percent)
com.	Continuous time interval of a single activity.	Activity	activity (int—enum)
(deprecated) com.	Total calories consumed over a time interval.	Activity	calories (float—kcal)
com.	Total calories expended over a time interval.	Activity	calories (float—kcal)
com. .	Instantaneous pedaling rate in crank revolutions per minute.	Activity	rpm (float—rpm)
com. .	Instantaneous wheel speed.	Location	rpm (float—rpm)
com.	Distance covered since the last reading.	Location	distance (float—meters)
com.	Heart rate in beats per minute.	Body	bpm (float—bpm)
com.	The user's height, in meters.	Body	height (float—meters)
com.	The user's current location.	Location	latitude (float—degrees) longitude (float—degrees) accuracy (float—meters) altitude (float—meters)
com.	Food item information	Nutrition	nutrients (Map<String,—calories/grams/IU) meal_type (int—enum) food_item (String—n/a)
com.	Instantaneous power generated while performing an activity.	Activity	watts (float—watts)
com.	Instantaneous speed over ground.	Location	speed (float—m/s)
com.	Instantaneous cadence in steps per minute.	Activity	rpm (float—steps/min)
com.	Number of new steps since the last reading.	Activity	steps (int—count)
com.	The user's weight.	Body	weight (float—kg)
com.	A user's continuous workout routine.	Activity	exercise (int—enum) repetitions (int—count) resistance type (int—enum) resistance (float—kg)

			duration (`int`—milliseconds)

Table 1: Fitness data types for instantaneous readings

Data types for aggregate data

These data types are defined as public fields of the `DataType` class. Their field names start with the `AGGREGATE_` prefix.

Data Type Name	Description	Permission	Fields (Format—Unit)
`com.`	Total time and number of segments in a particular activity for a time interval.	Activity	activity (`int`—enum) duration (`int`—ms) num_segments (`int`—count)
`com.`	Average, maximum, and minimum beats per minute for a time interval.	Body	average (`float`—bpm) max (`float`—bpm) min (`float`—bpm)
`com.`	A bounding box for the user's location over a time interval.	Location	low_latitude (`float`—degrees) low_longitude (`float`—degrees) high_latitude (`float`—degrees) high_longitude (`float`—degrees)
`com.`	User's nutrition intake during a time interval.	Nutrition	nutrients (`Map<String,`—calories/grams/IU) meal_type (`int`—enum) food_item (`String`—n/a)
`com.`	Average, maximum, and minimum power generated while performing an activity.	Activity	average (`float`—watts) max (`float`—watts) min (`float`—watts)
`com.`	Average, maximum, and minimum speed over ground over a time interval.	Location	average (`float`—m/s) max (`float`—m/s) min (`float`—m/s)
`com.`	Average, maximum, and minimum weight over a time interval.	Body	average (`float`—kg) max (`float`—kg) min (`float`—kg)

Table 2: Fitness data types for aggregate data