Actinfo: Information Platform for Physical Activity

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Abstract

This work presents the development and assessment of Actinfo, a new information platform for the management of physical activity (PA) data. Built using a full-stack of open-source JavaScript technologies (MEAN), this platform is both a repository of PA studies and a tool for performing a number of operations on actigraphy files. Actinfo provides visualizations of relevant statistics from information in PA studies, as well as tools for comparing PA data from different studies. Data in Actinfo is modelled after the FHIR standard for healthcare information exchange, to ensure interoperability with clinical data. To validate the the accuracy of the data processing tools implemented, a comparative study was carried to compare computed PA time indicators and compliance with PA recommendations between two studies: a population of adult patients of type II diabetes, i.e. the study "D2FIT" (n=73) and a sample of the adult population of the municipality of Lisbon, i.e. the study "ProjCML" (n=69). It was possible to conclude that a lower percentage of participants in study D2FIT attain sufficient physical activity (18% vs. 35%), and that subjects in this study average lower sedentary times per day (71.89% vs. 72.12% of accelerometer wear time), less time in moderate to- vigorous-intensity PA per day (3.99% vs. 4.88% of accelerometer wear time) and a higher number of interruptions in sedentary behaviour (10.04 vs. 9.64 breaks/hour of sedentary time). In summary, it was possible to achieve a functional prototype of a PA data management platform with good usability.

Keywords: Physical activity, actigraphy, web platform, MEAN stack, FHIR

1. Introduction

The effect of physical activity (PA) in the health of individuals has been studied for decades and motivated the development of more robust methods for exploring the PA-health relationship. Current research often relies on the use of accelerometers (usually integrated in an activity monitor, called an actigraph) for the objective measurement of physical activity. These devices, which emerged in 1980s and 1990s, and are now commercialized in a larger scale (Troiano et al., 2014). The availability and accuracy of such tools has made it easier to profile PA, not only at the level of the individual, but also at the scale of a population, allowing the categorization of PA across a group of subjects. However, new tools also imply more data and, with that, the need to properly process, store and extract relevant information from that data.

In research facilities, such as the Exercise and Health Laboratory (EHLab, Faculty of Human Kinetics, University of Lisbon), there is a growing tendency to perform statistical analysis over larger datasets, originating from the aggregation of population samples from multiple PA studies. This results in a rising need for systems that centralize the vast amount of information generated, storing it under internationally recognized standards, while at the same time allowing the analysis of over the stored data. Additionally, there is an interest in improving on certain features of the currently used software to score and validate actigraphy data.

Considering these challenges, the main objective of this work was the development, implementation and assessment of Actinfo, a new platform capable of storing, manipulating and visualizing actigraphy data from PA studies, while also providing tools for processing actigraphy files. Additionally, this work had the goal of conducting a proof of concept comparative study, using Actinfo, to compare the objectively measured PA profiles of two populations.

Two main contributions resulted from this work. The first is the functional prototype of Actinfo, a 2-in-1 system which acts both as a repository of PA studies and as a tool for processing actigraphy files. The second is a comparative study analyzing the distribution of PA time indicators between two adult populations, using Acinfo. This also allowed me to validate the platform as a tool for storing, processing and generating relevant statistical

information from actigraphy files and PA studies.

2. Background on physical activity

Hypertension, coronary heart disease, type II diabetes, stroke, colon and breast cancer and depression are some of the most common noncommunicable diseases (NCDs). Risk factors for NCDs include an unhealthy diet, smoking, overweightness, high blood pressure and cholesterol, obesity and physical inactivity. Five of these are related with PA, which is a major independent and modifiable risk factor for NCDs.

Physical inactivity, on the other hand, is the one of the leading risk factors for global mortality (World Health Organization, 2010). Research has recently focused on the patterns of accumulation of sedentary time (ST), i.e., bouts of sedentary activity and breaks (interruptions in ST). Various studies have been conducted to investigate the connection between bouts and breaks in ST and subjects' physiology and health. Chastin et al. (2015) have demonstrated the positive effect that interrupting sedentary behaviour has in controlling adiposity and blood sugar levels. In fact, in patients suffering from certain NCDs, such as type II diabetes, breaking up ST has been shown to be a useful method to mitigate the negative effects of sedentary behaviours (Sardinha et al., 2017).

PA can be quantified through a variety of approaches. One approach is its quantification through energy expenditure, usually expressed in metabolic equivalent (MET) or kcal. The World Health Organization (2014) defines MET as "(...) the ratio of a person's working metabolic rate relative to their resting metabolic rate". As such, we can define one MET as the energy cost of sitting quietly, which in quantitative terms translates into a consumption of 1kcal/kg/hour. In an absolute scale, using METs as a reference, we can categorize PA as follows:

- Moderate PA, with an energy expenditure between 3 and 6 METs;
- Vigorous PA, corresponding to an activity being performed at an intensity greater than 6 METs.
- Light PA, with an energy expenditure between 1.6 and 2.9 METs;
- Sedentary behaviour, for activities with a cost $\leqslant$ 1.5 METs.

The World Health Organization details the recommended amounts of PA, for different age groups, in the "Global Recommendations on Physical Activity for Health" (World Health Organization, 2010):

- **Children and youth aged 5 to 17 years old**: A daily accumulation of a minimum of 60 minutes of moderate- to vigorous-intensity PA (MVPA, i.e., PA that is at least of moderate intensity) is recommended for this age group;
- **Adults aged 18 to 64 years old**: Adults falling in these range of ages are recommended an accumulation of 150 minutes minimum of moderate PA per week or a minimum of 75 minutes of vigorous PA accumulated during the week (or a combination of both);
- **Adults aged 65 years old and above**: the WHO recommends either at least 150 minutes of moderate intensity PA or 75 minutes of vigorous PA (or a combination of both).

Actigraphy is a non-invasive monitoring method for human activity, being typically used for objectively measuring PA. In a given study for assessing PA, participants wear an actigraph, during a given period of time, which records the wake-time activity of the subject.

Among the various manufacturers for these devices, one stands above the rest: Actigraph Corp (Actigraph, LLC; Ft. Walton Beach, FL). The main sensor for registering activity is a built-in accelerometer. Actigraph's accelerometers have been thoroughly validated since their release (Troiano et al., 2008). In newer devices, the data is sampled at a user defined frequency, ranging from 30 Hz to 100 Hz, with every sample being stored in the device. Downloading data produces a raw, *.gt3x data file. This file is then filtered and accumulated into epochs of user-determined size (for example, 15s, 30s or 60s), through Actilife (Actigraph's software for processing actigraphy data) creating an *.agd file (containing, amongst other information, accelerometer data).

The *.agd files are in the open SQLite format[1]. It is, therefore, easy to develop code to process information stored in these files. The activity data of interest corresponds to a numeric value of "counts", i.e., Actigraph Corp.'s units of measurement of activity. Different values of counts translate into different levels of PA intensity. Several cut point sets are implemented in Actilife in order to map counts to sedentary activity, light PA, moderate PA or vigorous PA, according to the age of the subjects.

The "Evenson Children" cut point set is employed at the EHLab for actigraphy data from children and youth aged 17 or younger, segmenting PA into classes as follows:

- Sedentary activity, for values in the range 0 to 100 CPM;

[1] SQLite: `www.sqlite.org`

- Light PA, for counts between 101 and 2295 CPM;
- Moderate PA, for values between 2296 and 4011 CPM;
- Vigorous PA, when activity counts are higher than 4011 CPM.

The ”Troiano” cut point set, used for adults aged 18 or older, contains the following categories:

- Sedentary activity, for values in the range 0 to 99 CPM;
- Light PA, for counts between 100 and 2019 CPM;
- Moderate PA, for values between 2020 and 5998 CPM;
- Vigorous PA, when activity counts are higher than 5998 CPM.

3. Supporting technology

The platform was developed following a 3-tier software architecture for web applications, structured in the following logical modules:

- A presentation tier, accessible through a web browser, which acts as the client, and through which information is presented via a graphical interface to end users;
- An application tier (or application server), containing the core logic driving the application;
- A data tier (also referred to as the database server) for handling database functions.

I built Actinfo based on the MEAN stack (MongoDB, Express, Angular, Node.js), a full-stack of open-source JavaScript technologies for web development (Louridas, 2016).

To ensure interoperability with clinical data and data integrity, the FHIR[2] standard for healthcare information was used to model data in the platform, whenever possible. Although Actinfo is, at its current stage, oriented towards PA research, I followed this standard, as it provides a solid, internationally used data model which safeguards the support for the integration of clinical and health data in future versions of the platform. Since MongoDB is a document-oriented database which provides schema flexibility, integration with FHIR is possible, by modeling documents after FHIR resources, in the JSON (JavaScript Object Notation) format. Since documents in MongoDB are grouped in collections, only the ones created specifically for PA data need to follow the FHIR standard.

[2]FHIR: `https://www.hl7.org/fhir/`

Actinfo is currently hosted in a SSL protected domain. A SSL certificate was emitted for the platform and installed in the server, allowing the use of the HTTPS protocol for secure communication over the network. I also implemented a platform specific user authentication system in Actinfo, to control access. When a registered user successfully logs in to the platform, a JSON Web Token (JWT) is generated, which allows for the secure transmission of information between parties as a JSON object. Furthermore, because it is digitally signed, the information can be trusted and verified.

4. Actinfo

Figure 1 shows the logical data model for the database. Five different collections of entities exist in this model. Each collection has an entity type:

- ***user***: a collection of information profiles for the registered users, including the access credentials for navigating the platform.
- ***researchStudy***: the collection for data from physical activity (PA) studies, its documents modelled after FHIR's *ResearchStudy* resource, plus some additional fields. A *researchStudy* establishes a many-to-many relationship with the documents in the *user* collection via embedding of the *user* references in the *researchStudy* document, under the ”userPermissions” field. Additionally, documents in this collection contain embedded documents for groups of study participants, establishing a one-to-many relationship.
- ***studyGroup***: documents with this entity type appear in the form of embedded documents in the *researchStudy* collection. They contain metadata resulting from grouping the study participants.
- ***researchSubject***: a collection for data from participants from the PA studies. The documents in this collection were modelled after the *ResearchSubject* FHIR resource. This is the collection in which the outputs resulting from operations on actigraphy files are stored, i.e., the PA time indicators (sedentary time, time in light PA, time in moderate- to vigorous-intensity PA and breaks/bouts) and other information extracted from the files. The ”groups” field in the documents of this collection allow the establishment of a many-to-many relationship with the *studyGroup* the subject belongs to, via one way embedding.
- ***file***: a collection for metadata for actigraphy files uploaded to the platform. A *file* establishes a many-to-one relationship with the *re-*

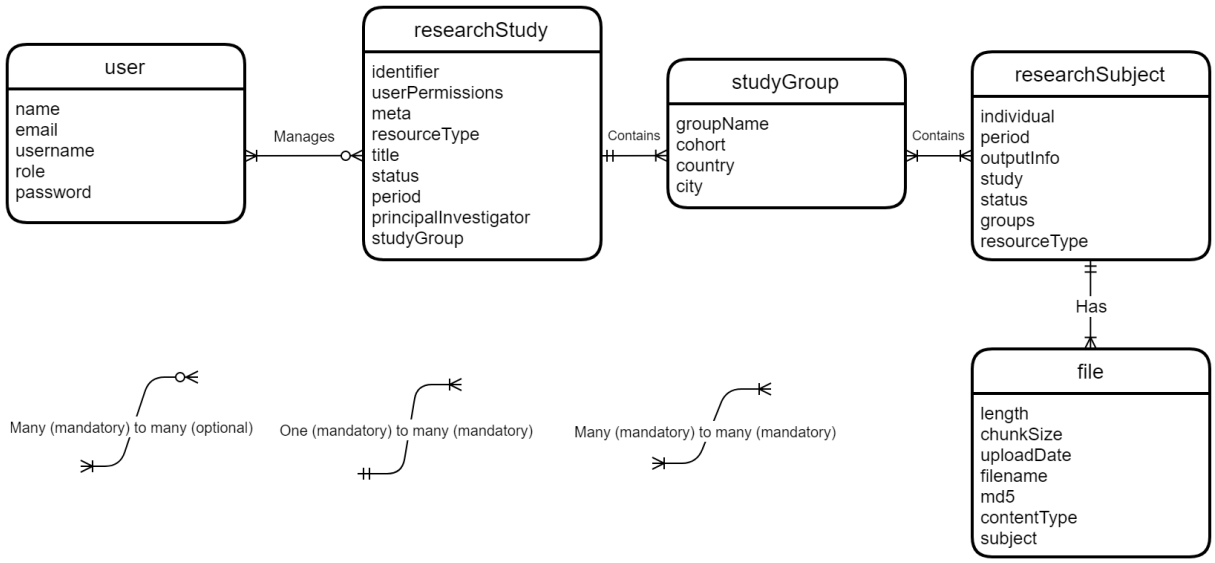


Figure 1: Data model for Actinfo.

searchSubject, by including a field which references the subject the file belongs to.

In the platform's web server, I developed methods to perform all the required tasks for CRUD (Create, Read, Update, Delete) operations on documents in the *researchStudy*, *researchSubject*, *user* and *file* collections, as well as process actigraphy data. When an user makes a request, via, for example, the click of a button, an Angular service is triggered to send this HTTP request to the application tier, where the appropriate responses are generated and sent to the client.

As for the presentation tier, it sits on top of various Angular components, each rendering a different page the user has access to, in HTML+CSS. For more complex visualizations, such as charts for the distributions of PA time indicators, open-source libraries, such as D3.js[3] and Chart.js[4], were used to generate HTML plots from JavaScript arrays created using the implemented methods.

User interface

Actinfo supports two different types of user accounts, according to the role attributed during account creation: administrator accounts, with the "admin" role and researcher accounts, with the "researcher" role. These result in different sets of features being available to different types of users.

Administrator accounts have the ability to register new users in the platform and manage registered users. After successful login, the user is redirected to the dashboard (Figure 2 (a)), listing all the registered users, with options to edit their information or remove them from the platform. Additionally, there is also a "New user" option available.

As for researcher accounts, Figure 2 (b) shows the dashboard presented upon login. A number of operations are available to users.

A tool for processing actigraphy files is available to users. Upon choosing the option to validate the *.agd files, three main operations take place in the application tier, based on user-selected settings:

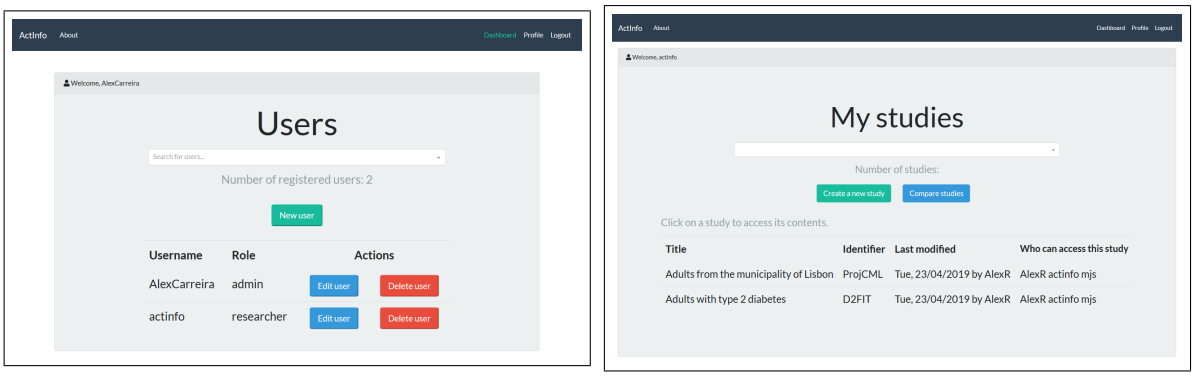
1. **Wear time validation**: to remove periods of non-wear time from the analysis, based on standardized criteria for accelerometer reduction settings (International Children's Accelerometry Database (ICAD), 2017). A period of time in the *.agd time series is considered as non-wear time (i.e., time during which the participant was not wearing the monitor) if a minimum of 60 minutes of consecutive zero-value activity counts is observed. Form this definition, a day is considered valid if it accumulates at least 600 minutes of valid wear time. Lastly, at the file level, a file is considered valid if a minimum of three valid days occur, one of them being a weekend day.

2. **Application of cut points**: based on the chosen cut point set, the duration of the time periods in each level of PA intensity is calculated, resulting in the accumulated time in each intensity, for each valid day. Options for cut point sets include the "Troiano" and "Evenson" cut point sets, similar to the ones in Actilife, and a "Custom", user defined, cut point set.

3. (if selected) **Computation of bouts/breaks**: for each valid wear time period, bout detection takes place, according to the user selected bouts. The total number of detected bouts and

[3] D3.js: `https://d3js.org/`

[4] Chart.js: `https://www.chartjs.org/`



(a) **(b)**

Figure 2: Administrator (a) and researcher (b) dashboards.

the accumulated duration are saved, for each selected bout.

Following this validation, users are redirected to the output page showing detailed information for all the validated files. This includes the values for the computed time indicators by day, bouts/breaks and more general information, such as the subject's age and gender. Users can also export these results no an Excel file and save the validation outputs to the database.

Users also have options for the visualization of statistics for the PA time indicators, generated from saved validation results of files within a study, or compare this information between studies. The interface for both these features is similar, the main difference being the datasets used. The page is divided in two sections: "Demographics" and "Physical activity and sedentary time". Additionally, options to filter the data by gender and/or by age group are also available to users. An example of these visualizations is presented later in Section 5.

5. Assessing Actinfo

Actinfo is currently hosted in a FCCN virtual machine, managed by INESC-ID, available at the domain `https://actinfo.inesc-id.pt`. The platform resulted from a collaboration with the EHLab, who provided actigraphy data and user feedback, which allowed to validate and evaluate Actinfo and the accuracy of its tools.

Conformity

During the development of Actinfo, I collected input from researchers at the EHLab regarding the various functionalities as they were being implemented. This feedback served to determine exactly how each one of the main features of the platform should operate, i.e., what was required of each functionality. By assessing the conformity of Actinfo's features with the requirements, I was able to conclude that, when features did not perform exactly as expected, this was mainly due to the lack of customization options and need for the redesign of certain pages, for improved readability and user experience. For these features, the main aspects regarding their implementation status are the following:

- The interface lacks options to group studies;
- Permission management should be more complete, allowing users to also remove access from a specific study.
- Options to manage files in studies are incomplete and somewhat limiting of the options to explore comparisons between multiple datasets;
- The tool for accelerometer wear time validation lacks customization options;
- Some adjustments are needed in the interface for visualization of the validation output to make it more intuitive;
- The exported Excel file should contain more information.

Usability

Actinfo's users can open a website-tailored version of the System Usability Scale (SUS, Brooke, 1996) questionnaire, which was embedded in the website's navigation bar. The SUS is a 10-item questionnaire which provides a "quick and dirty" method to evaluate usability of various systems. The questionnaire contains 10 Likert items, i.e., questions with five levels of response, ranging from "strongly disagree" to "strongly agree". The seven registered users with the "researcher" role were asked to answer the survey after testing Actinfo's various features. The answers from those users were collected to obtain the SUS score. As per the method

Table 1: SUS scores of Actinfo's evaluation (n=7)

Item	Mean score	Mean SUS item score
"I felt very confident using the website"	4.33	3.33
"I found the various functions on this website were well integrated"	4.67	3.67
"I think that I would like to use this website frequently"	5	4
"I thought the website was easy to use"	4.33	3.33
"I would imagine that most people would learn to use this website very quickly"	5	4
"I thought there was too much inconsistency on this website"	1.67	3.33
"I needed to learn a lot of things before I could get going with this website"	2.33	2.67
"I found the website unnecessarily complex"	1.67	3.33
"I found the website very cumbersome to use"	1	4
"I think that I would need the support of a technical person to be able to use this website"	1.67	3.33
Final SUS score	87.5	

originally described by Brooke, 1996, for every positively connoted item, the expression $x - 1$ was applied, x being the average of all users' scores, ranging from 0 ("strongly disagree") to 4 ("strongly agree"); for every negatively connoted item, the expression $5 - x$ is used; the scores for all items are then added and multiplied by 2.5, yielding the final SUS score. A score of 87.50 out of a possible 100 was obtained for Actinfo, resulting from the individual scores presented in Table 1. The score obtained for Actinfo falls within the range of scores for categories between "Excellent" and "Best imaginable" (Bangor et al., 2009), which can be used as an indicator of having achieved a prototype with good usability.

Comparative study

To demonstrate the platform's potential in, not only comparing PA metrics and their distribution between different populations, but also in computing those parameters, I conducted a comparative study, using the various tools implemented in Actinfo. To this end, accelerometer data from two populations was used, from two different studies conducted by the EHLab: one study collected accelerometer data with the goal of assessing physical activity amongst the adult population of the municipality of Lisbon (study ProjCML), and the other used actigraphy data collected as part of a clinical trial aiming to determine the effect of different physical exercise protocols in biomarkers in adult patients of type II diabetes (study D2FIT).

Using these two datasets, the platform's tools for computing physical activity time indicators were employed to obtain average ST per day, average time in MVPA (moderate- to vigorous-intensity PA) per day and average number of breaks per hour of sedentary time, from uploaded *.agd files. The platform also allowed comparing the distribution of subjects meeting the WHO's recommendations for physical activity.

Data preparation prior to the comparison involved three major steps:

1. I uploaded actigraphy files from a total of 174 subjects to the platform (80 corresponding to the D2FIT study and 94 for ProjCML).

2. Using the implemented tools for validating the files, I performed a preliminary screening analysis. Invalid files were excluded from the study (i.e., files with missing data or files which did not meet the minimum wear time requirements). A total of 142 files remained, which were used for the analysis (i.e., 73 files corresponding to the D2FIT study and the remaining 69 from the ProjCML study).

3. I employed Actinfo's tools for computing PA time indicators: the wear time validation feature, application of cut point sets and break computation. Regarding the cut point set, since, in both studies, the participants are adults, the "Troiano" cut point set was used.

Actinfo's "Compare studies" tool was used to produce the visualizations for the various computed metrics. Figure 3 shows the first section of the comparison page, with demographic data for the population. Figure 4 shows the second section of the page, with the distributions of compliance with PA recommendations, ST per day and daily time in MVPA. Figures 5 and 6 show the same information after filtering by males and females, respectively. Lastly, using Actinfo's "Export" function, I obtained the average daily number of breaks per hour of sedentary time. The outputs are summarized in Table 2.

The distributions obtained in the "Demographics" section indicate similar age distributions for both

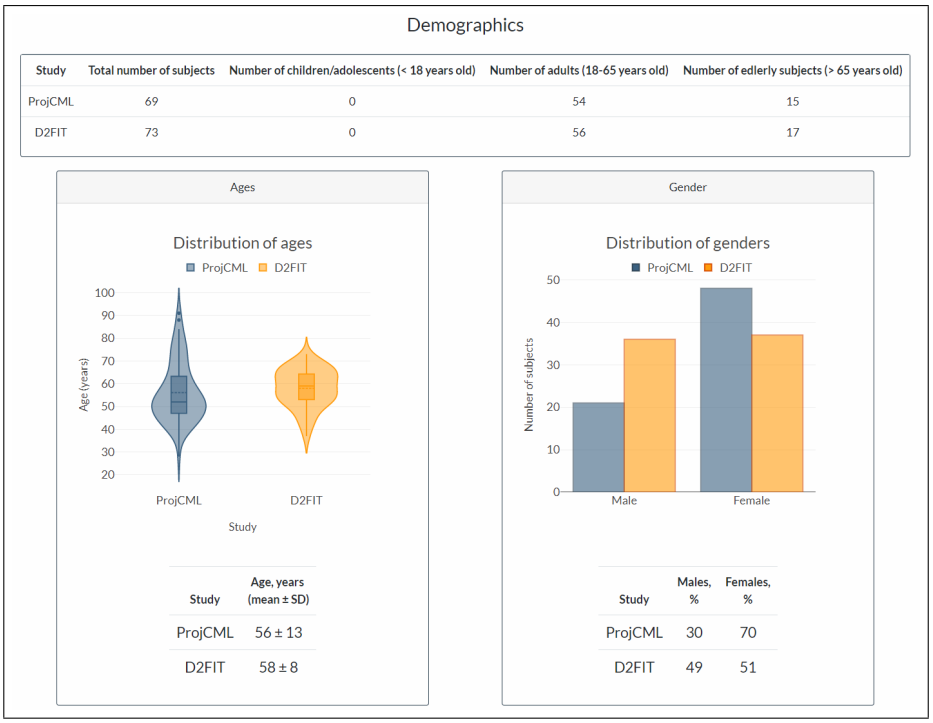


Figure 3: Demographics for the analyzed population.

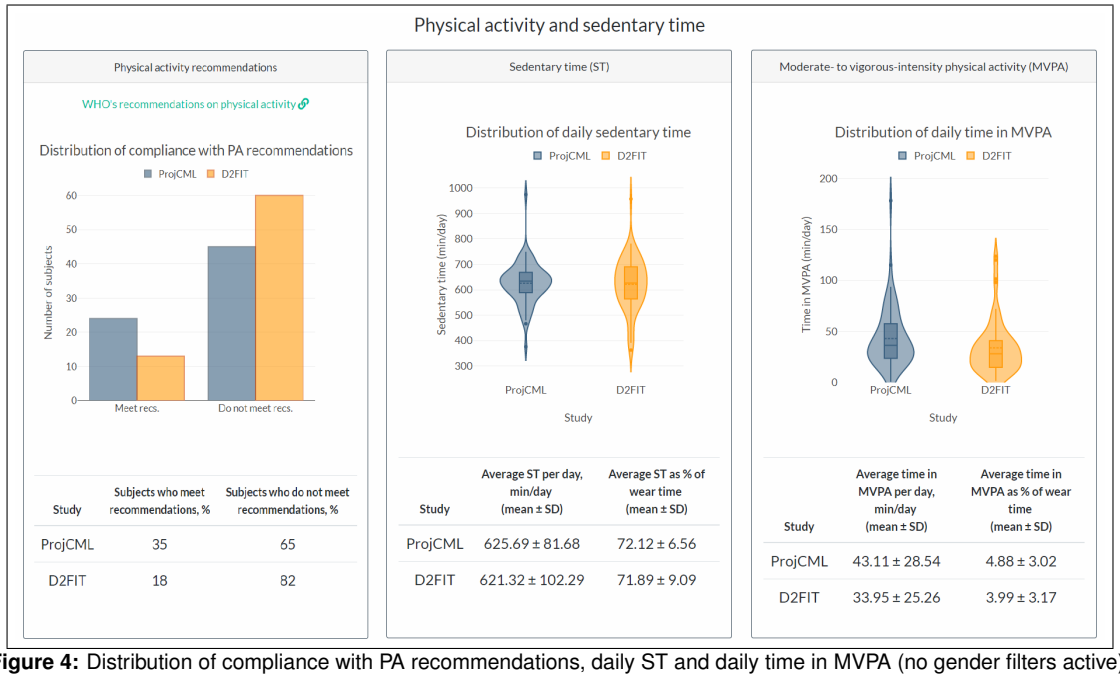
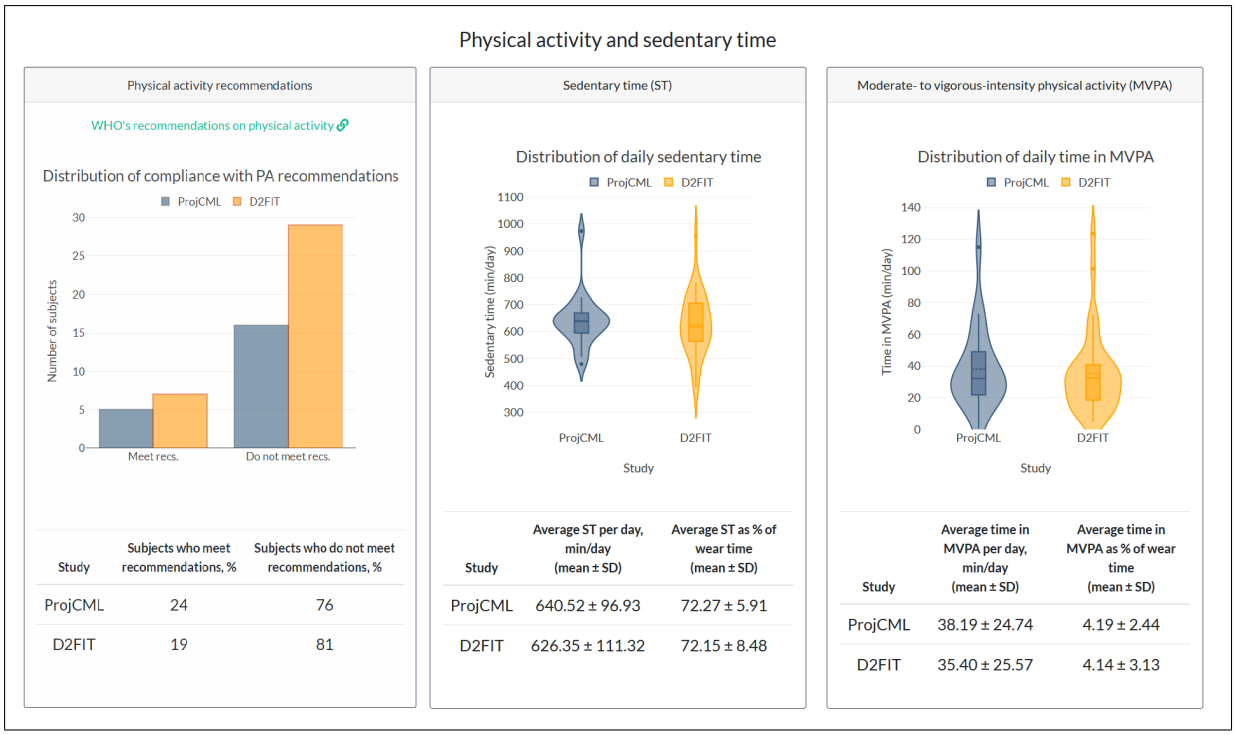


Figure 4: Distribution of compliance with PA recommendations, daily ST and daily time in MVPA (no gender filters active).

studies, with a high density of participants close to the late adulthood stage of life (around 60 years old).

Comparing the studies in terms of the distribution of subjects who meet the recommended amounts of PA, patients of type II diabetes show a much lower percentage of subjects attaining sufficient PA than participants from ProjCML. When comparing different genders in both studies, using Actinfo's gender filters, while in ProjCML a higher percentage of females than males meet the recommendations, in study D2FIT the opposite happens. The large discrepancy observed between the percentage of males and females who meet the recommendations in ProjCML may be attributed to the uneven distribution of subjects across genders, in this study.

As for ST, participants in study D2FIT average lower sedentary times per day when compared to subjects in ProjCML, both in males and females. A

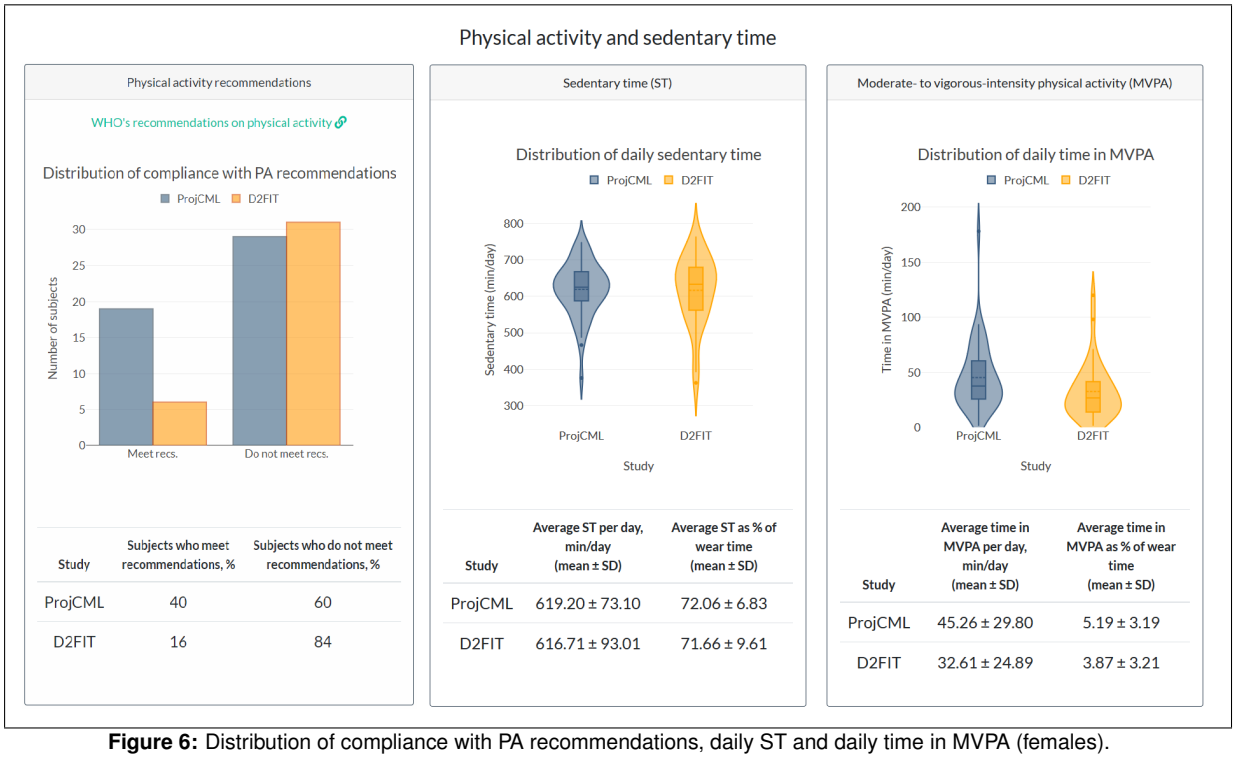


Study	Subjects who meet recommendations, %	Subjects who do not meet recommendations, %
ProjCML	24	76
D2FIT	19	81

Study	Average ST per day, min/day (mean ± SD)	Average ST as % of wear time (mean ± SD)
ProjCML	640.52 ± 96.93	72.27 ± 5.91
D2FIT	626.35 ± 111.32	72.15 ± 8.48

Study	Average time in MVPA per day, min/day (mean ± SD)	Average time in MVPA as % of wear time (mean ± SD)
ProjCML	38.19 ± 24.74	4.19 ± 2.44
D2FIT	35.40 ± 25.57	4.14 ± 3.13

Figure 5: Distribution of compliance with PA recommendations, daily ST and daily time in MVPA (males).



Study	Subjects who meet recommendations, %	Subjects who do not meet recommendations, %
ProjCML	40	60
D2FIT	16	84

Study	Average ST per day, min/day (mean ± SD)	Average ST as % of wear time (mean ± SD)
ProjCML	619.20 ± 73.10	72.06 ± 6.83
D2FIT	616.71 ± 93.01	71.66 ± 9.61

Study	Average time in MVPA per day, min/day (mean ± SD)	Average time in MVPA as % of wear time (mean ± SD)
ProjCML	45.26 ± 29.80	5.19 ± 3.19
D2FIT	32.61 ± 24.89	3.87 ± 3.21

Figure 6: Distribution of compliance with PA recommendations, daily ST and daily time in MVPA (females).

higher interquartile range was also found in the former. Additionally, it was observed males in both studies spend more wear time in sedentary behaviours, when compared to females.

Observing the plots and metrics for time in MVPA, patients of type II diabetes spend less time in moderate- to vigorous-intensity PA per day than subjects in ProjCML. A lower interquartile range was also found for study D2FIT. Comparing males and females, while in study ProjCML the latter spend a higher percentage of wear time in MVPA, the opposite happens in study D2FIT.

Lastly, comparing the number of breaks/ST hour between studies, an overall higher number of in-

Table 2: Number of breaks per hour of sedentary time

Study	Number of breaks/ST hour (mean ± SD)		
	No filter	**Males**	**Females**
ProjCML	9.64±3.60	9.91±3.80	9.52±3.49
D2FIT	10.04±4.82	8.86±4.45	11.21±4.88

Table 3: Mean absolute error for each computed PA time indicator.

Study	MAE		
	ST (min/day)	**MVPA (min/day)**	**Number of breaks/day**
ProjCML	0.11	0.13	29.06
D2FIT	0.11	0.14	26.06

terruptions in ST was obtained for study D2FIT, with the exception of males in this study, who show lower breaks/ST hour in a day when compared to males in study ProjCML. Additionally, while in ProjCML a higher number of breaks/ST hour is observed in males, male participants in D2FIT present fewer interruptions in ST than females in the same study.

To assess the validity of the obtained results, I processed the same files used for the described analysis in Actigraph Corp.'s Actilife software, selecting equivalent parameters for wear time validation and data scoring. Table 3 presents the obtained error values for each PA time indicator. The mean absolute error (MAE) was computed, instead of simply comparing the averages for the time indicators with the ones obtained from Actinfo, to obtain a measure of the error associated with the outputs from the platform.

Regarding the deviations observed in ST and MVPA, these can be explained by different implementations of the wear time validation cycles. Although Actilife's code is proprietary, comparing the SQLite time series in *.agd files with the data scoring export file the software produces, it is possible to understand some filtering of the data occurs during the validation. This translates into a lower wear time than that of which we gather from the actual data, which explains the slight error in the sedentary times and time in MVPA per day when comparing Actinfo's outputs with the export from Actilife.

Regarding the number of breaks/ST hour, possible explanations for the high MAE point, once again, towards different implementation strategies when computing this parameter. As per Actigraph Corp.'s own documentation (Actigraph Corp., 2018), breaks are computed by subtraction of the time in sedentary bouts from the total time, without taking non-wear time into consideration. With Actinfo, however, break and bout calculation was implemented by detecting bouts and/or breaks only for valid wear time periods.

6. Conclusions

The centralization of actigraphy data, paired with statistical analysis and validation features makes Actinfo a great tool for research in the field of PA. With Actinfo, it is possible to improve PA analysis workflows while also contributing for the interoperability with clinical information and reusability of the data, which is stored in a standardized manner. However, the current version of the platform still has some limitations, which could be addressed in future iterations via the following improvements:

- **Encryption of the database**: data stored in MongoDB should be encrypted, as an extra measure of protection. Currently, only the paid-for version of MongoDB, named MongoDB Enterprise, supports "Encryption at rest", which would solve this problem. Alternatives ways to encrypt the data could be researched.
- **Data from multiple sources**: ultimately, Actinfo should allow for the integration of data from multiple sources, not just from actigraphy files. In future iterations, users could be able to cross PA data with information from sources such as imaging exams (e.g.: x-rays and DEXA scans for bone density), physical performance tests or medical exams from which health indicators could be extracted.
- **Expand on FHIR**: if Actinfo moves towards making use of clinical information, interoperability with clinical data could be improved by using more FHIR-specific fields in the database documents.
- **Energy expenditure**: the tools for processing actigraphy data are able to extract height and

weight information from the *.agd files, but this information is not used. A feature for computing energy expenditure could be implemented in future versions of the platform, making use of the height and weight information.

- **Read *.gt3x files**: to access the true raw data recorded by the activity monitor, we would need to be able to operate on the data stored in the *.gt3x files. A tool for extracting raw accelerometer data from these files could be implemented in Actinfo.

- **Expand the database**: the platform could benefit from having a larger dataset of PA files and studies available to its users, allowing for more comparisons and meta-analysis between different populations.

- **Improve the data model**: it could be useful to expand the current data model. In fact, it could be beneficial to allow the support of a different type of user account for study participants, who could be able to upload their actigraphy data directly to the platform. Additionally, the model could account for the separation of the datasets from the study, allowing users to create studies from files already uploaded to the platform. The model would also need to be more generalized and support new relationships between collections of entities.

In summary, I was able to achieve a functional prototype of a PA management platform with good usability. To assess the platform, I evaluated its conformity and usability. Additionally, I conducted a comparative study, as proof of concept of Actinfo's capabilities for data analysis. The platform was also validated against Actigraph Corp.'s software, regarded as the "de facto standard" for for analyzing objectively measured PA via actigraphy. Future versions can take advantage of Actinfo's modular architecture to easily improve the platform.

7. Acknowledgement

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