# LEARNING TOMORROW: VISUALISING STUDENT AND STAFF'S DAILY ACTIVITIES AND REFLECT ON IT

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## Abstract

Learning Tomorrow is a program at the Amsterdam University of Applied Sciences (AUAS) that stimulates the use of digital tools to enable a more personal, informal and collaborative way of working within the university. Moreover, it raises awareness of sedentary behavior, to support its students and staff physical activity. This paper discusses a first study that was conducted to understand the current state of physical activity within the context of the AUAS. With the use of QS (Quantified Self) technology, data was gathered from a 4-week field trial in which 24 participants (both students and teachers) used a Fitbit and a GPS tracker. The collected data was analyzed to find out whether the use of specific technology and tools would lead to a better overview of people's physical activity. This study also aims to evaluate the effectiveness of using a visual analytics tool [11] to facilitate insight into how this daily physical activity data yields to reflective learning in order to promote continuous learning and improve future experiences. The results indicate that the combination of both GPS tracking and a Fitbit for stated period, with only a limited number of participants, can deliver a clear overview of physical activity in general and more specifically of routes that are taken. However, results also indicate that data alone is not everything either. Contextual understanding was found to be a vital addition.

Keywords: Quantified Self, Fitbit, GPS Tracking, Visual Analytics, Physical Activity, Reflective Learning, Visual Learning Patterns, Learning Tomorrow.

## 1 INTRODUCTION

During the past five years people all over the world have been recording data about themselves and their surroundings (self-tracking), producing a flux of information with accelerometers. Technology, such as accelerometers, can be supportive in this process and very useful in assisting people with increasing their physical activity. These can objectively capture body movement and provide information on the total amount, intensity, duration and frequency of physical activities performed, in order to motivate people to improve their life. However, with the increasing amount of generated and collected data available, the efficiency of their use becomes more challenging. As a consequence, applying accelerometry as a tool to assess daily physical activities is a rapidly evolving field of research.

"12:45, restate my assumptions. 1. Mathematics is the language of nature. 2. Everything around us can be represented and understood through numbers. 3. If you graph the numbers at any system, patterns emerge. Therefore: there are patterns everywhere in nature." - Maximilan Cohen, number theorist and main character of π (1998).

This research focuses on daily activity data, (of both students and teachers) specifically, involving walking. Walking is the most frequently reported type of leisure-time physical activity [16]. Although walking is important to our daily lives, we have little understanding about how much people walk outside leisure-time contexts. And how many steps per day does an average person make? According to Tudor - Locke (Ph.D. Department of Exercise and Wellness) and Bassett Jr. (Ph.D. Department of Health and Exercise Science) men have an average of 7192 steps per day and women have an average of 5210 steps per day. The global increase in overweight and obesity is attributable to a trend towards decreased levels of physical activity [5]. Very often technology, in the form of computers and televisions, is blamed for this general decrease in physical activity [10]. Nonetheless technology may also be very useful in assisting people to increase their physical activity. By making people aware of their sedentary behavior, they might want to learn from it, reflect and change it [7].

The history of self-tracking using wearable sensors in combination with wearable computing and wireless communication already exists for many years, and also appeared, in the form of sousveillance back in the 1970s [13, 12]. This study aims to show that Quantified Self (QS) approaches can support reflective learning processes. QS uses various self-tracking methods to 'quantify' a persons approach to life and goals, often helping to see where things are changing, or need to change, to track progress around personal endeavors, in order to personalize our lives.

With the far-flung availability of cheaper self-trackers and Global Positioning System (GPS) trackers it is possible not only to record the numbers of steps but also people's movement. The Fitbit[1], a wireless activity tracker, can be seen as a first generation of self-trackers that can be 'dressed' with covers and ornamentation, for example, footwear covers for bicycling, or watertight wristband covers for swimming. This type of devices produces data at an incredible rate, leading to a significant information overload and new requirements for the analysis process. Visual Analytics [11] could be a solution.

Visual analytics (VA) can be described as 'the science of analytical reasoning facilitated by interactive visual interfaces'. To be more precise, visual analytics is an iterative process that involves information gathering, data pre-processing, knowledge representation, interaction and decision-making, by combining the analytic capabilities of the computer and the abilities of the human analyst [18]. It focuses on managing big volumes of information by integrating human judgment through using visual representations and interaction techniques in the analysis process. Analysis of these massive volumes of data is a place of deciding for various domains, e.g. decision-makers, analysts, or in another sense, people interested in rapidly gaining insight from this flood of data. As raw data in most applications have little value themselves, we want to be able to extract the information contained in it, moreover interact with it, learn from it and thereafter reflect on it. Visual analytics seems an ideal solution for the information overload problem and for facilitating the QS community's data analysis.

This study was conducted according to the visual analytics model proposed by [11] (see figure 1), in order to turn data information overload into an opportunity. This model describes the iterative process of data gathering and exploration, hypothesis building, visualization design and analysis, and the gaining of insight by directly interacting with the gathered data, in order to reflect upon the data.

This paper discusses the ongoing research on the use of technology in order to motivate people to become more physically active. A study conducted to understand the current state of physical activity within the context of the Amsterdam University of Applied Sciences (AUAS) will be introduced and discussed. Furthermore an objective of this study was to evaluate the effectiveness of using a visual analytics tool to facilitate insight into how this daily physical activity data yields to reflective learning, also known as learning by returning to and evaluating past work performances and personal experiences in order to promote continuous learning and personal future experiences [3]. All part of the AUAS program Learning Tomorrow[2].

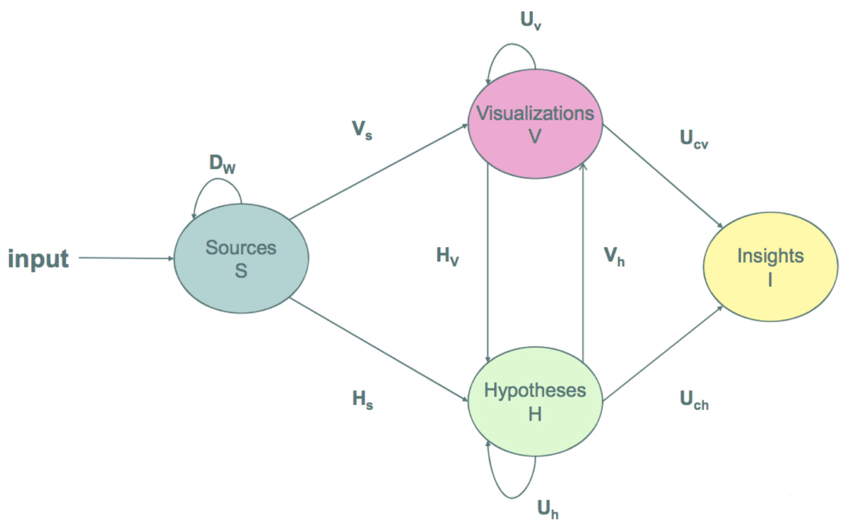


Figure 1: Keim et al. (2008) [11] *processing of data* model that describes the iterative process of VA and the interaction between Sources (S), Visualizations (V), Hypotheses (H) and Insights (I).

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[1] http://www.fitbit.com/zip.

[2] https://learningtomorrow.hva.nl/nl/Paginas/Visie- Learning-Tomorrow.aspx.

The remaining sections of this paper will give an overview of some relevant related work (2), within the following ranges; self-tracking, visual analytic tools, and reflective learning. Thereafter the research question will be proposed (3), the methods (4) and data (4.3) used during this experiment are presented. Followed by the results (5), its conclusions (6) and lastly future work (7).

# 2 RELATED WORK

In this section we consider a more in-depth reading of self-tracking and reflective learning.

## 2.1 Self-tracking

Self-tracking devices, like sensors, smart phones/tablets etc. increasingly helps individuals gain more insight in the physical aspects of their lives. Recent advances in small inexpensive sensors and low-power processing have enabled new technologies that use on-body sensing and machine learning to automatically track and figure out people's activities throughout the day [6]. Since the introduction of the Quantified Self by Gary Wolf and Kevin Kelly a few years ago, increasingly more people are using such self-tracking tools and collecting data via devices such as Fitbit, or Jawbone UP[3]. Jawbone UP consists of a wrist-worn motion detector that interfaces with an iPhone app, allowing the user to track his/her daily physical activity. Stand-alone wearable tracking devices, like Fitbit, but also the Nike Fuelband[4] and the Misfit Shine[5], are self-monitoring devices that display visualizations of the physical activity and behavior of its user.

Keeping track of our lives is nothing new. For example, many athletes have been carefully and precisely monitoring personal metrics for decades. The power of self-tracking moreover, is even more profound. Collecting data can help to change behavior by using self-tracking tools. Feedback loops can be established [12], because when we keep track of something we see how the data matches up with what we would like to happen, and we can use that knowledge to modify our actions. The effect of feedback on attempts to change behavior is well accomplished. DiClemente, Marinilli, Singh, and Bellino [7] state that personalized feedback increases the effectiveness from exercise programs to interventions for problem drinkers. Feedback is important and powerful. This feedback can also be internal, as one gets positive feedback from their body after a couple of runs. And what to think of the community effect? Christakis and Fowler [5] state that social networks can influence our behavior, and community ties have direct effects on people's behavior, for example as a motivator through competition with friends when scores are being ranked like with a Nike Fuelband and the Fitbit. Figurerunning[6] is also a good example that encourages you to get creative and go outside while running and getting fit. Figurerunning is not about speed or distance, but about the patterns being made by the GPS tracker.

The ease with which these new tools make self-tracking possible combined with the increasing possibilities of sharing data and gaining more insight from this data, results in more and more people finding it useful to quantify their lives. Self-tracking plays an extensive role as it aims at presenting the application of visual analytics for analysis of daily activity data, and therefore it can have a new full impact on the visual analytics process. This experiment is an attempt to perpetuate the purpose of visual analytics in analyzing these data.

## 2.2 Reflective learning

According to Boud [2], reflective learning is learning by returning to and evaluating past work performances and personal experiences in order to promote continuous learning and improve future experiences. But a consolidated model that describes the role of technologies, such as Fitbit, is missing out on reflecting [14]. Our growing interest in self-tracking results in a mixture of tools to gather data in order to self-reflect and monitor ourselves, with the aim of knowing more about our own habits, behavior and recurrent patterns. QS approaches are more pragmatic, whereas reflective

[3] https://jawbone.com/up.

[4] http://www.nike.com/us/nikeplus-fuelband.

[5] http://www.misfitwearables.com.

[6] http://figurerunning.nl.

learning is driven by theories. Figure 2 shows a model for the technological support of reflective learning centered in the model of [14].

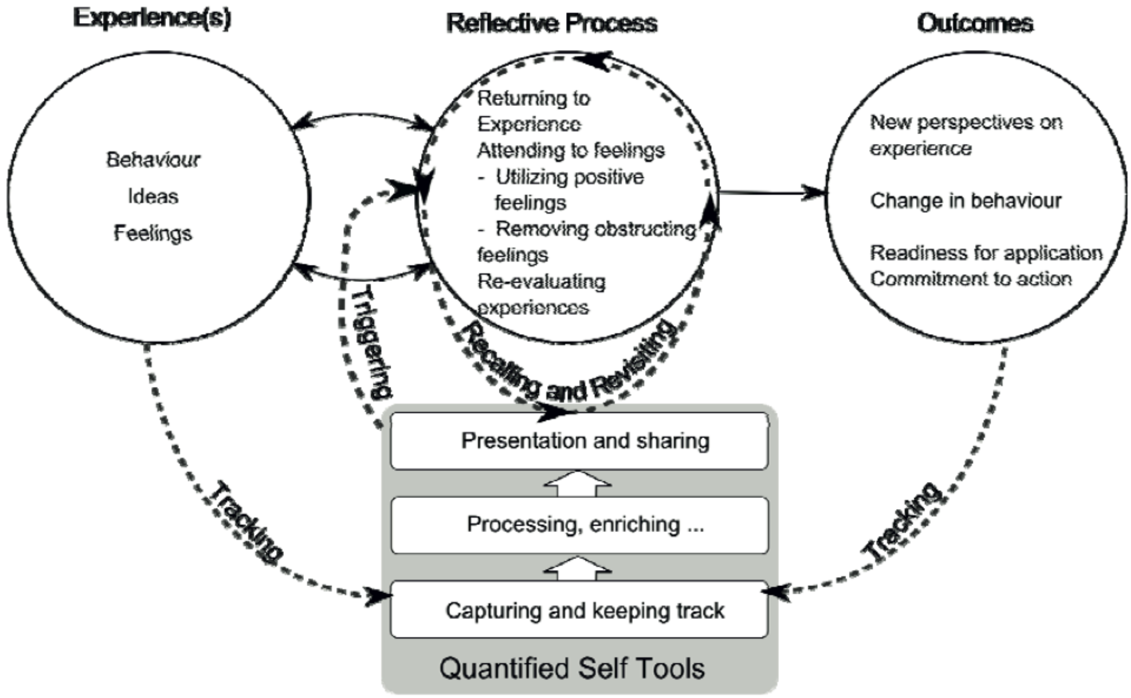


Figure 2: Rivera-Pelayo et al. [14] model that shows the role of the three QS potentials in the process of reflective learning.

This model shows how QS approaches can reinforce the process of learning by reflection and alters the design of new QS tools for informal learning purposes. Technology can be used as a tool and be supportive in providing resources for reflection. The user can be enabled to see things from multiple perspectives and be guided in the process of reflection. A record of events can be looked at several times. Moreover, technology allows one to see more than one could possibly see without. Sensor technologies record, detect and represent data of experiences otherwise not available to human perception. Thus reflecting upon these events will let you experience a different viewpoint out of one's own scope.

## 3 PROBLEM STATEMENT AND RESEARCH QUESTION

In this section we consider a more in-depth reading of self-tracking and reflective learning. What can the various devices for capturing our activities and the programs to analyze them actually tell us? What our habits are? Maybe even mental and psychological states? These are all factors that influence our everyday behavior, our mind and our psyche: what if we were able to control them, or even manipulate them? Are we then able to optimize our experiences and gain more insight in order to have, for example, a more (physically) active or vivid life, and thus reflect on it?

The proposed research is based on the before-mentioned literature and investigates whether a Fitbit in combination with a GPS tracker are able to assist people in increasing their physical activity, by reflective learning: by raising awareness of people's sedentary behavior, and learning by returning to and evaluating past work performances and personal experiences. This in order to promote continuous learning and improve future experiences.

For this particular study the following research question is stated:

> *'Does a Fitbit in combination with a GPS tracker enable us to map daily habits of students and teachers in the context of the AUAS and can it serve as input for raising awareness of their sedentary behavior, in order to assist them in increasing their physical activity and reflect upon it?'*

The following section will elaborate on how this study has been performed.

# 4 METHODS

This study was conducted according to the visual analytics model proposed by [9]. This model describes the iterative process of data gathering and exploration, hypothesis building, visualization design and analysis, and the gaining of insight (see figure 1). To find out how to present analysis of Fitbit data for its user to gain optimal insight, both quantitative and qualitative research were conducted. In this section we consider a more in-depth reading of self-tracking and reflective learning.

## 4.1 Study design

24 participants, 13 staff members and 11 students, of which 14 were female and 10 were male, aged 19-68 *(M=35.1)*, were recruited through convenience sampling [3]. All Amsterdam University of Applied Sciences (AUAS) affiliated participants, from all seven domains, were given a unique number from 0 to 23 to easily distinguish them while processing the data and to prevent privacy invasion in terms of anonymity.

During a period of two months, 24 students, teachers and support staff from the seven domains of the AUAS were monitored for this experiment. From the beginning of February till the end of March the participants carried a Fitbit Zip (an always-on electronic pedometer, that in addition to counting steps also displays distance travelled, calories burned, current intensity, and time of day) with them. Furthermore, for a period of two weeks within those two months, they also carried a GPS Canmore GT-750(L) Bluetooth tracker (a device to determine the precise location of a person, or another asset to which it is attached and to record the position of the asset at regular intervals). With this tracker it was possible to see geospatial patterns that translated into classrooms without walls and digital communication services.

All data was presented on an interactive visual analytics dashboard, in order to see if there were recognizable patterns amongst the participants, and to see if using these Quantified Self tools leads to gaining more insight from the gathered data in order to reflect upon, and create awareness for a more active lifestyle. With this information, it is also possible to see how Keim and Rivera-Peloya's models can be mapped on the collected data.

## 4.2 Materials

In order to answer the research question, both quantitative and qualitative research was performed. There are several research instruments: the step counts from the Fitbit ZIP, the tracking of the GPS tracker (for more detailed information see the used devices (see appendix). Lastly, some small interviews were conducted to gain more an idea of what data is desirable to present at an interactive visual analytics dashboard, for gaining insight. Before giving out the Fitbit ZIP and the GPS tracker to the participants a questionnaire was conducted. General information about age and area where the participants live was gathered. Also questions about the participants' media usage, how they travel between various locations, and some questions about, if, and what kind of sports they are doing, were asked.

## 4.3 Data sources

A good dataset has several characteristics such as: high volume, of known pedigree, multivariate, etc. This experiment consists of two main datasets that have the above-mentioned characteristics:

1. Fitbit data;
2. GPS data.

### *4.3.1 Data gathering and processing*

These two datasets have different characteristics and need to be processed in different ways. Each dataset has been retrieved from its respective sources and thereafter processed so that it could be analyzed using Tableau Desktop[7] and Google Earth8[8] (free version 7.0.2.8).

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[7] http://www.tableausoftware.com/.

[8] http://earth.google.com/.

### 4.3.2 *Fitbit dataset*

The Fitbit dataset consists of a plain text data file, listing timestamps for each specific user. The overall list of timestamps contains 60,055 entries, after removal of entries where no steps where counted. Of all participants the data from the 1st of February 2013 until the 28th of February 2013 was used. The Fitbit API9[9] was used to download the specific content.

Table 1: Fitbit data and its contents. Each variable is associated with a participant.

| Data file | Data | Type |
|---|---|---|
| `timestamp` | timestamp | Ratio |
| `steps` | amount of steps | Ratio |
| `id` | user id | Ratio |
| `gender` | gender | Nominal |

An overview of the types of data that are listed for each of the data files can be found in above-mentioned table:

**Timestamp** Timestamps are used as a sequence of characters or encoded information identifying when a certain event occurred, an indication for behavior;
**Steps** Some participants are more active than others. Assuming that making more steps means that people are more aware of their sedentary behavior, this could affect people's physical activity;
**Id** While not that interesting for high-level analysis, including the id's in visualizations may aid us as it allows for verifying findings with other sources and zooming in to a specific user in a later stage, for example, by conducting an interview afterwards;
**Gender** It would be interesting to research whether there is a significant difference in gender to see if there is a disparity in the number of steps taken between men and women.

### 4.3.3 *GPS dataset*

One person was removed from the original dataset due to the Netherlands scope of this research. This person was living in India, Bangalore at the moment of the research. Therefore the GPS dataset consists in the end of positions of 23 participants, which have been GPS-tracked ranging from February to March 2013. Within this timeframe, for each participant, one week was chosen at random.

Each record in the database includes the date and time, the latitude, longitude and altitude of the position and a few additional fields such as index, line ID. The temporal space of the records is every 10 seconds.

To facilitate analysis of movement data, initial pre-processing in the data was performed. The [1] approach for analysis of movement data has been used. Sequences of records corresponding to absence of movement, i.e. where the distance in space to the next recorded position is below a threshold, were removed. The remaining dataset had exact 17,777 positions left. Furthermore the timestamp was initially set to GMT+1:00, this was adjusted to GMT+2:00.

### 4.3.4 *Data Analysis and Visualisation*

The Fitbit analyses were made primarily using Tableau Desktop, a software application that allows interactive visualizations of data to be easily created using a drag-and-drop interface. In the patterns that emerge from reviewing the collected data of the participants, one should be able to see if users can learn from their gathered data and reflect upon it.

Furthermore, Google Earth has been used as a virtual globe, map and geographical information program. It is one of a growing number of geobrowsers, widely employed for the visual synthesis of

[9] http://dev.fitbit.com/.

spatial data and for interacting with these data [16]. The data was specified in a KML format, an XML markup language in which graphical encoding and interactions can be defined for interpretation.

## 5 RESULTS

The Fitbit data was visualised in various graphs. The results show for example a difference in activity measured in steps between female and male (see figure 3), as well as students and teachers, both in amount of steps and in peek moments.

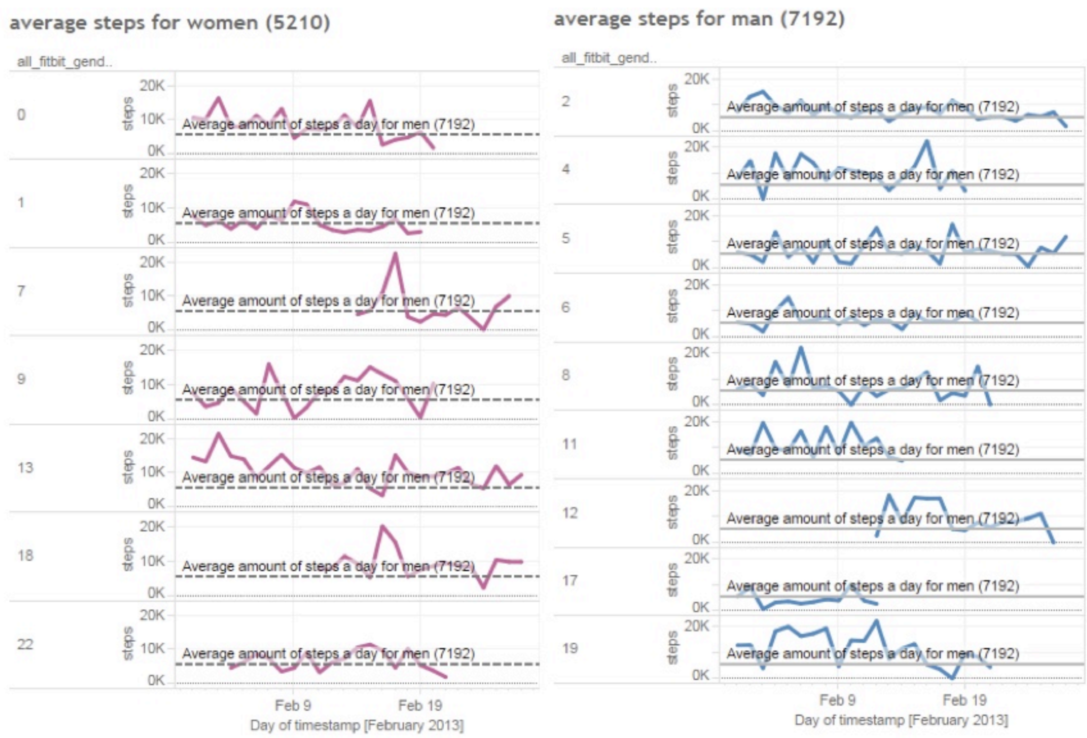


Figure 3: Result on average steps of men and women in the month February. At the left the average amount of steps for women are represented and at the right one can see the average amount of steps for man. The dotted line within the graphs visualizes the average.

On both February 9th and 24th figure 4 shows a drop in physical activity for both students and teachers. After analysing the weather on those specific days, it was discovered that it was snowing those days in February.

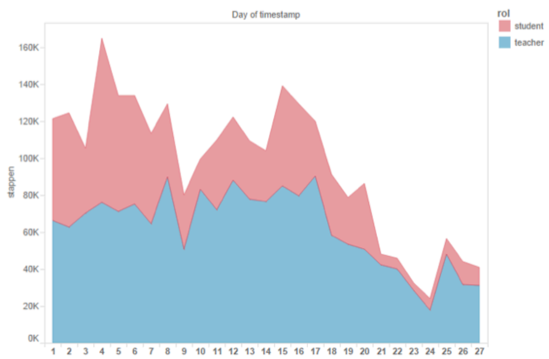


Figure 4: Amount of steps for both students and teachers in February 2013 *(N=24).*

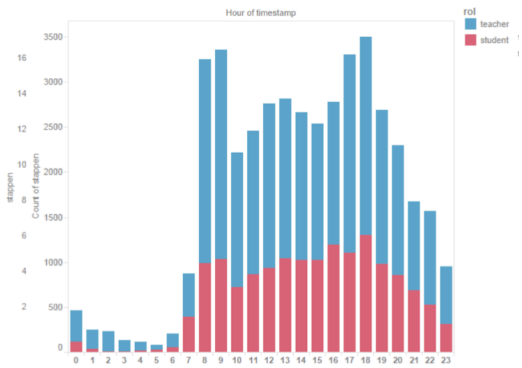


Figure 5: Average amount of steps for students and teachers on weekdays *(N=24)*.


Figure 6: Screenshot of visualization of GPS data and routes by students (blue) and teachers (pink). One can already recognize the contours of the city Amsterdam.

## 6 DISCUSSION

It is good to point out that the gathered Fitbit data consists of a certain timeframe, namely the month of February. In order to make a more thorough analysis, the dataset should include a longer timeframe as well as in various seasons. This would allow us to identify patterns over a longer period. Also, some participants stopped using the Fitbit after a couple of days. The next experiment should take drop-outs into account. Furthermore, the GPS trackers were also used for a relatively short period of time (one week). If used for a longer time, this would allow us to identify patterns over a longer period.
Assuming that QS tools can be pointed out to assist people in realizing their desired outcomes, there will always be a lack of understanding on how to identify the various situations and context in which they will be used.

With this study it was attempted to find arguments to track and visualize physical activity by students and teachers in order to gain insight into which of this data is relevant for reflective learning, for a Fitbit user, in order to promote continuous learning and improve future experiences.
Only little research has been done on the use of Fitbits widely, as well as reflective learning in combination with a QS tool, because it is still a relatively young technology. The collection of daily activity data through QS approaches offers a rich source of data that has not been available for learning processes before.

## 7 CONCLUSION

The results indicate that the combination of both GPS tracking and a Fitbit for a period of 2 months with only a limited number of participants, can deliver a clear overview of physical activity in general and more specifically of routes that are taken. What remains unclear is why there are differences between for example female students and female staff members in physical activity. It seems that asking questions still remains important in order to uncover the why's and how's behind QS type of data. Data is always embedded in a specific context and in understanding that context one can see its limits and its biases. To get more information out of this data it is necessary to talk to the people involved and get their individual stories and their particular context to find out how they are engaging with that specific technology (like a FitBit) in their everyday lives. Therefore we can conclude that merely measuring and tracking students and staff members is not enough, and one needs to discover who the person is behind the data.

This study was part of ongoing research on the role of data gathering in positively influencing physical activity amongst students and staff members in the context of the AUAS's Learning Tomorrow program. This was a first exploratory experiment, illustrating that this type of data can provide valuable insights in the status of physical activity. Next experiments are planned that focus on the effect on awareness and on the actual change in physical activity based on that awareness.

In conclusion, the results of this study emphasize the importance of a dialogue between the analysts and self-tracking users in the analytical process. Additionally iteratively enhance the analytical process supported by visual analytics, in order to filter and customize the visualizations at ones preference. We see the future rosy, the data world is still very much in its infancy, and the debate about what it is exactly, where it is going, and how everyone will get there, has just started.

## 8 FUTURE WORK

Future work involves the design and implementation of new QS tools that will empirically validate the presented model (figure 2) to support reflective learning. Also future work can include a longer experiment where more comparisons can be made. Besides further heuristic evaluations of the VA tools into daily analytical activities of self-tracking can be conducted, to provide a user with enough information in order to promote continuous learning and improve future experiences.

## 9 ACKNOWLEDGEMENTS

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# 11 APPENDIX USED HARDWARE

## 11.1 FitBit ZIP

This wireless activity tracker exists of a Zip, wireless sync dongle, battery, battery tool and a clip to attach it to you. It tracks ones daily activity, syncs data realtime to a computer or smartphone, and one can check his/her progress, steps taken, calories burned distance traveled. It uses a three-dimensional motion sensing technology similar to the device that is used in the Nintendo Wii.

The Fitbit is made of silicone and a metal clip, wireless sync dongle to mobile and laptop, replaceable battery, LCD (liquid crystal display). There is tap control of the device, it is both Windows and Mac compatible, and the battery life is 4-6 months. The Zip uses a MEMS 3-axis accelerometer that measures motion patterns to determine calories burned, distance traveled, and steps taken. MEM 3-axis accelerometer means that it can detect acceleration, inclination and vibration by measuring the motion in the x-, y- and z-axis simultaneously. The device is not waterproof. It's sizes are 35,5mm x 28mm x 9,65 mm and it weights 8 grams. One can access the Fitbit dashboard online[10]. There is also an iPhone application available and various API's to grab the data[11].

[10] http://www.fitbit.com/.

[11] http://dev.fitbit.com.


Figure 7: FitBit Zip.

## 11.2 GPS Tracker

The Canmore GT-750(L) Bluetooth, is a lightweight, wireless GPS Logger with Bluetooth's transmission technology and manifold usage possibilities. It can be used with a tablet, smartphone and notebook. The battery lasts up to approx. 13 hours. KML code will be used as a file format to display geographic data in an Earth browser, such as Google Earth, Google Maps, and Google Maps for mobile. KML code is the output of the GPS tracker device[12]. The tracker has a bluetooth interface of operation. The device weights 60 gram (including battery).

Figure 8: GPS tracker.

[12] https://developers.google.com/kml/documentation/.