A Quantified-Self Framework for Exploring and Enhancing Personal Productivity

Gary White  
School of Computer Science and Statistics,  
Trinity College Dublin,  
Dublin, Ireland  
whiteg5@scss.tcd.ie

Zilu Liang  
School of Engineering  
Kyoto Uni of Advanced Science  
Kyoto, Japan  
z.liang@cnl.t.u-tokyo.ac.jp

Siobhán Clarke  
School of Computer Science and Statistics,  
Trinity College Dublin,  
Dublin, Ireland  
siobhan.clarke@scss.tcd.ie

Abstract—A variety of self-tracking applications and devices have been developed in recent years to support users in tracking their weight, calories eaten, physical activities, sleep and productivity. The availability of all this data from multiple streams provides a rich environment for experimentation that allows users to improve certain aspects of their lives such as losing weight, getting better sleep or being more productive. In this paper we propose a framework that guides users to define, track, analyse, and control goals for better personal productivity. We present the outcome of a single-subject case study that was implemented over one year based on the proposed framework for academic productivity. This pilot study demonstrates how longitudinal multistream self-tracking data can be leveraged to gain actionable insights into personal productivity.

I. INTRODUCTION

Increase in the availability and reduction in cost of wearable devices has allowed people to self-track multiple streams of data in an ecologically valid environment. Activity trackers such as the Fitbit Charge 3, Samsung Gear Fit2 Pro and Apple Watch Series 4 are now used by a large number of consumers. More recent devices have explored additional activities that users may want to track, such as connected inhalers, smart insulin pens and asthma monitors. These novel streams of data can be integrated and mined to gain insights that enable preventive actions in managing chronic conditions such as diabetes and asthma (e.g. ADAMM Asthma Monitor can detect the symptoms of an asthma attack before its onset).

The rise in popularity of these devices has led to the development of communities of quantified self and lifelogging [1]. This is a movement to incorporate technology into data collection on aspects of a person’s daily life, with the goal of improved physical, cognitive and/or emotional health. A lot of work has been done on the physical output especially with the emergence of P4 medicine: predictive, preventive, personalised and participatory [2]. In this work we focus on the less addressed aspect of cognitive output, which we track as productivity.

Productivity is a difficult metric to track compared to physical signals such as heart rate or length of sleep, which have exact numerical values. No consensus has been reached in terms of how personal productivity should be defined and measured. Many daily activities can be classified into different levels of productivity depending on the purpose and outcomes of doing the activities. For example, using Facebook would be considered an unproductive activity for most people except those who use it for their jobs, such as marketing and social network researchers. Establishing a standard scheme for productivity classification of these activities is thus one of the biggest challenges in productivity research. To address this challenge, some software applications have endeavoured to standardize the productivity classification based on user feedback. Assuming that most jobs now involve using a computer or phone, these applications automatically track the time spent on different software or websites and then derive productive/unproductive time of a user [3]. The availability of these productivity data together with other contextual information such as sleep and physical activity makes it possible for users to explore how factors in their lifestyle may influence personal productivity.

Nevertheless, many people who conduct self-tracking or life logging tend to focus mostly on the data collecting stage, with stages of data archiving, analysis and interpretation often overlooked because of a lack of skills necessary to conduct such a processes [4]. This explains the call for the improvement of health literacy skills among lifeloggers [5]. When multiple metrics are being tracked from different devices it can also make it hard for users to aggregate and visualise what variables are having an impact on the output. As the wearable devices that we use are a combination of physical objects with virtual representations and services, we can use augmented reality to superimpose virtual information about smart objects on a user’s view of the real world [6]. Services in the environment can also provide additional contextual information such as weather and air quality [7], [8]

In this paper we propose a framework that guides people to design and perform a full cycle of self-tracking activities for better productivity, from defining the goals, to collecting and analysing the data, to reflecting on behavior change. We highlight how computing technologies (e.g. augmented reality, mobile applications, activity wristbands) and data analytics (e.g. statistics and data mining) can be used for data collection and analysis. We also present the outcomes of a single-subject case study over a year as an example of how to adapt and implement the framework to personal needs. The preliminary results offer rich implications to further systematic research.
on how to design personal informatics technologies to help people achieve better productivity.

II. RELATED WORK

A. The Quantified-Self and Personal Informatics

In quantified-self, people use a variety of tools (e.g. Excel sheets, diary, mobile applications, wearable devices) to collect data from a range of inputs (e.g. food consumed, quality of surrounding air), states (e.g. mood, heart rate, skin conductance, blood oxygen levels, length and quality of sleep) and outputs (e.g. physical or cognitive status).

The rise of the Quantified Self movement gave birth to a new research field named personal informatics that focuses on empowering individuals to gain actionable insights from their self-tracking data for better health and well-being. A number of studies have looked at the opportunities and challenges for personal informatics technologies to help people improve sleep [9], [10], lose body weight [11], and manage chronic conditions [12]. Several recent studies also attempted to frame the importance of self-tracking data for better health and well-being. A number of studies have looked at the opportunities and challenges for personal informatics technologies to help people improve sleep [9], [10], lose body weight [11], and manage chronic conditions [12]. Several recent studies also attempted to frame the importance of self-tracking data for better health and well-being.

B. Track

Productivity research has also examined factors associated with employee productivity [24]. These studies found that both organizational factors (e.g. job characteristics [25], autonomy [26], office environment [27]) and individual factors (e.g. motivation [28], work engagement [29], psychological status [30]) matter. A recent study in quantified workplace has looked at the effect of workplace metrics (noise, colour, air quality, self-reported mood) in two European offices of a research organisation [31]. The activity tracking was self-reported with employees able to choose their activities from a pre-populated set of 8 work related activities e.g. meetings, writing, programming, administration. However, there was no option for “relaxing” or “checking twitter”, this can give unrealistic productivity data where users are engaged in work related activities for the entire day without taking a break.

III. QUANTIFIED PRODUCTIVITY FRAMEWORK

A. Define

In the framework we define being productive as being engaged in domain-specific tasks that lead to the accumulation of domain-specific expertise needed for significant academic contributions [32]. Productivity can be tracked using a personal diary in Excel or automatic screen time recording applications such as RescueTime. RescueTime classifies computer software programs into productive ones and unproductive ones based on whether a user can build up domain-specific expertise by using the program. In the context of academia, application such as Mendeley, PyCharm, and TextStudio are considered as productive programs as they are mostly used for reading papers, conduct data analysis and write manuscripts. Gaming and social network service programs are considered unproductive because they are mostly used for entertainment. Following this logic, the time that spent using the productive programs is counted as productive time and vice versa.

In addition to the tracking of productivity itself, there are a large number of factors that can influence productivity, e.g. sleep, physical activity, social interaction, illness, working environment, stress, management style. The difficulty of tracking these factors varies. Factors such as sleep and physical activity can be easily tracked using consumer wearable wristbands at high data granularity. External factors such as ambient temperature, humidity and lighting can be tracked using portable devices, which are less common to find. Psychometric factors such as stress, emotion, and social interactions are not easy to track as they are difficult to quantify in the first place. When precision and data granularity is not important, a simple way to track these factors is to use diary-based subjective rating.

B. Track

Table I summarizes some of the monitoring tools that can be used to track productivity and contextual factors defined in

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1https://www.rescuetime.com/
the previous subsection. The methods for tracking productivity and lifestyle factors range from manual tracking through self-reporting to automatic tracking using consumer wearable devices. The hurdle of manual tracking is lower than automatic tracking, but it requires significant commitment from the user to log data regularly at the specified time. For example, there are a number of mobile applications that allow users to track their productivity based on self-rating. A five point scale is usually used with the lower and upper bound representing very unproductive and very productive respectively. Nevertheless, the downside of this method is the low sampling rate and the subjectivity of the data collected. On the contrary, automatic tracking using consumer wearable devices (e.g. Fitbit) or mobile applications (e.g. SleepAsAndroid) allow users to collect multiple physiological and behavioural metrics objectively, longitudinally and at high sampling rate (e.g. heart rate every 5s, minutes sedentary, activity calories, minutes of deep sleep each night). However, accuracy and missing data are the downside of this method. In a real situation, a combination of these two methods is usually adopted to reduce cost and to increase the variety of lifestyle factors that can be tracked.

It is also worth noting that some factors can be tracked using several methods. For example, sleep duration can be tracked either using Excel sheets, mobile applications such as SleepAsAndroid and consumer wristbands such as Fitbit. Multiple methods can be used concurrently to measure a single factor to ensure the reliability of measurements.

C. Analyse

One of the problems with quantified self is the focus on the collection of data and initial viewing without generating actionable insights that can be used to improve the productivity of the user. Previous studies have highlighted the difficulty for laymen users to gain insights from self-tracking data [33]. This can happen as analysing such a huge amount of personal data requires domain knowledge on data analytics techniques ranging from basic statistical calculation to advanced data mining. As a result, quantified selfers usually rely on intuitive observations of the time series plots of interested data to answer questions like "what happened" and "why it happened", leaving the subsequent questions like "how can I do better" unanswered.

Health analytics in clinical settings usually consists of four level of analysis. In what follows we present an adaptation of the analytics levels to productivity tracking and the analysis techniques that can be applied at each level.

- Level-1 analysis: standard report (e.g. how was my productivity during the past month?), query drill-down (e.g. was I productive yesterday?).
- Level-2 analysis: statistical analysis [33] (e.g. what are the factors that influence my productivity?).
- Level-3 analysis: anomaly detection [10] (e.g. on which days I was not productive?), time-series predictive modelling [34] (e.g. would I be more productive if I sleep longer?).
- Level-4 analysis: association rule mining [35], optimization (What should I do to achieve the best productivity?).

The basic level analysis can be done in Microsoft Excel. More complicated statistical analysis, data mining and modelling can be done using specialized software including R, Matlab, Python. This type of analysis is challenging for laymen as they lack expertise in related domains. The design of personal informatics technology should address this challenge by developing automated data analysis tools that hides the technical details from the users.

D. Improve

One of the easiest actionable ways to improve productivity is to follow the association rules that are generated by applying association rule mining to the data collected about the user. These rules provide a simple customised guideline for users to achieve increased productivity based on their own data. One of the problems with association rules mining is that they can be bounded by the users’ lifestyle context [36].

The optimal ranges of lifestyle factors given to a user are based on their current lifestyle rather than being absolute ideal ranges. In order to explore personal optimal ranges of a given lifestyle factor, it is necessary to carefully design the self-tracking experiments in a controlled manner [13], [14], [15]. This allows the user to explore ranges for factors they didn’t realise were an issue e.g. not getting enough sleep.

Another approach that could be utilised for user improvement would be to use data from other users with similar characteristics (based on age, fitness, sleep and job) to provide recommendations to the user. For example, telling a user that other similar users are achieving better productivity by increasing sleep time to 8 hours. This can be viewed as a recommender tasks where the goal is to recommend changes to factors that have increased other users productivity. This avoids the problem of having an unproductive user that does not experiment with variations on factors such as sleep time that may be effecting their productivity. This could lead to them getting stuck at a local optimal productivity level and not achieving their global optimal.

Augmented reality can also be used to improve engagement and enjoyment of various activities such as physical exercise. Applications such as Pokemon Go\(^2\), Fitness AR\(^3\) and Zombies,Run!\(^4\) have been successful in engaging users.

\(^3\)https://itunes.apple.com/us/app/fitness-ar/id1274233318
\(^4\)https://zombiesrungame.com/

<table>
<thead>
<tr>
<th>Factor</th>
<th>Method</th>
</tr>
</thead>
<tbody>
<tr>
<td>Productivity</td>
<td>RescueTime, Self-reporting</td>
</tr>
<tr>
<td>Sleep Quality</td>
<td>Fitbit Tracker, SleepAsAndroid</td>
</tr>
<tr>
<td>Physical Activity</td>
<td>Fitbit Tracker</td>
</tr>
<tr>
<td>Diet</td>
<td>MyFitnessPal</td>
</tr>
<tr>
<td>Weight</td>
<td>Fitbit Aria, KAMTRON Smart</td>
</tr>
<tr>
<td>Social Interaction</td>
<td>RescueTime, Self-reporting</td>
</tr>
<tr>
<td>Illness</td>
<td>Self-reporting doctor visits</td>
</tr>
<tr>
<td>Working Environment</td>
<td>Noise, temperature, light sensors</td>
</tr>
<tr>
<td>Management Style</td>
<td>Self-reporting</td>
</tr>
</tbody>
</table>
and encouraging more physical activity through gamification. Gamification of everyday tasks could be applied to other activities like coding or reading papers. For example, using ColdTurkey, users may set up writing goals (e.g. the number of words or pages typed) and will not be allowed to switch application until the goal is reached.

E. Control

Once the user has defined, tracked, analysed and improved their behaviour, it is necessary to sustain the changes to avoid falling back into old routines. Sustaining behavior change is challenging if there is lack of motivation. Users can leverage the notifications of self-tracking tools to stay aware of factors that lead to unproductive behaviour. For example, Fitbit wristbands push a notification to users if no steps are detected in the last hour. Multiple tools can be combined to create an ambient personal productivity surveillance system by aggregating multiple sources of tracking data. Websites such as If This Then That can be used to integrate signals from multiple sources. For example, it can be integrated with Resuetime to block all distracting websites after 10 pm to achieve better sleep. It can also send a notification or block sites if you go over a time limit for a category e.g. over an hour on news websites.

Augmented reality (AR) can also be applied in the "Control" phase to support the lasting of behavior change. For example, it has been used to control the serving of food [37]. With increased integration from IoT devices [6] in the future you could get a notification when choosing a chocolate cake as your connected scales shows increased BMI and you have reduced physical activity today based on your Fitbit.

IV. A SINGLE-SUBJECT CASE STUDY

In this section we present the outcome of a pilot case study to demonstrate how the proposed framework can be implemented and adapted to personal needs. This study was conducted from 2018-01-01 until 2019-03-31 with a single subject.

A. Define

The goal of the subject was to explore how productivity may be associated to sleep and physical activity. Based on the findings of previous productivity studies [23], [31], the subject selected the following variables to track:
- Productivity: daily usage pattern of applications and websites.
- Sleep: total sleep time, total wake time, sleep efficiency, the ratio of each sleep stage (i.e. wake, light sleep, deep sleep, REM sleep), the total length of each sleep stage, the number of segments of each sleep stage, the average length of sleep cycle.
- Physical activity: calories burned, steps, distance, minutes sedentary, minutes lightly active, minutes fairly active, minutes very active, activity calories.

B. Track

In this study, RescueTime was used to track productivity on weekly basis. We checked the most used applications and websites to ensure that they were in the correct classification. Since our subject is a research student in computer science, the productive applications included reference manager Mendeley, programming IDE PyCharm, and text editor Texstudio, while the unproductive applications included music streaming platform Spotify and a game platform Steam.

Figure 1 shows the productivity data for over a year. The y axis is measured in seconds and each data point represents one week. We can see how specific dips in the amount of data captured match to external academic tasks such as attending conferences and also around extended public holidays such as Christmas. These are occasions where students typically spend less time on their laptop compared to a traditional work environment, which explains the clear drops in productivity.

Sleep tracking was done using the mobile application Sleep-AsAndroid and a Fitbit Charge 3 wristband. Tracking the same variable such as sleep efficiency through different tools provides an opportunity to compare the values that they report. Figure 2 shows the difference in sleep efficiency recorded between the two tools. The disparity was due to the fact that each tools used their own proprietary algorithm for sleep/wake detection [38].

C. Analyse

In total 65 weeks of sleep and productivity data were collected using SleepAsAndroid and RescueTime respectively. Fourteen weeks of activity and sleep data were collected using a Fitbit Charge 3.

We applied two analysis techniques to explore the relationships between lifestyle factors and productivity: Spearman’s correlation analysis (level-2 analysis) and association rule mining (level-4 analysis). Spearman’s correlation is widely used to explore the linear relationship of ordinal or categorical variables. Missing data were removed pair-wisely during the Spearman’s correlation analysis. Association rule mining is a data mining technique traditionally used for market basket
analysis [35]. It has been applied to many other areas including computer security [39], bioinformatics [40] and personal informatics [33]. Association rule mining can naturally handle missing data.

Spearman’s correlation analysis found statistically significant negative correlations in productivity to minutes very active ($r$=-.65, $P=0.011$), to the number of awakenings ($r$=-.72, $P=0.003$), and to the number of light sleep segments ($r$=-.59, $P=0.026$). Association rule mining identified 58 association rules between lifestyle factors and productivity, out of which 57 were associated to high productivity and 1 was associated to low productivity. The top five rules ranked by lift are listed in Table II. These rules emphasize the importance of sleep and maintaining light activity for increased productivity. More importantly, they give the user quantitative measurements to further experiment with and improve.

The analyses phase can also reveal interesting correlations, for example in Figure 3 we see that there is a clear relationship for this student between attending conferences and improved sleep efficiency. When the tracking beings at the start of the year the sleep efficiency is high, over 0.5. When the student returns from the the Percom conference in 2018 there is a noticeable decrease in sleep efficiency down to around 0.25. This is recovered slightly during the next conference but then decreases again after the conference until the week before attending the PerCom conference in 2019. We don’t have any exact justification for this as it could be due to a number of factors such as better beds, increased movement and social activities during conferences or reduced stress. However, the clear and specific correlation warrants further investigation.

D. Improve and Control

Based on the results obtained in the “Analyse” phase, the subject learned that productivity was associated to sleep duration as well as a mixture of sedentary and active behaviour. Aiming at maximizing productivity the subject is currently experimenting with pushing the limits of each of these factors to see how they effect productivity.

V. CONCLUSION AND FUTURE WORK

It is hard to boost personal productivity without gaining a quantitative understanding on the dynamics of productivity from day to day and under the influence of various contextual factors. In this paper, we have proposed a framework that can be used to plan and implement self-tracking activities for better productivity. We presented a single-subject case study for a research student in computer science to exemplify how the framework can be adapted to personal needs.

The major limitation of this work is that it focuses on one particular user. Although the framework that we outline can be used by multiple people who do most of their work on a computer. A more detailed study with a cross section of ages, occupations and health habits are needed to validate the framework and generalise any rules that can be applied to improve productivity. In future work, we plan to expand on this initial single-subject case study with more users from different countries using the framework that we have outlined.

ACKNOWLEDGMENT

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REFERENCES

<table>
<thead>
<tr>
<th>Rule</th>
<th>Productivity</th>
<th>Support</th>
<th>Confidence</th>
<th>Lift</th>
</tr>
</thead>
<tbody>
<tr>
<td>LengthAdjusted$=[55.8,57.7)$, Distance$=[7.2,20]$</td>
<td>Low</td>
<td>0.062</td>
<td>0.8</td>
<td>3.467</td>
</tr>
<tr>
<td>SleepDuration$=[59.2,70.3)$, DeepSleepRatio$=[0.215,0.276)$, MinutesFairlyActive$=[11.16,3]$</td>
<td>High</td>
<td>0.077</td>
<td>1</td>
<td>1.711</td>
</tr>
<tr>
<td>SleepDuration$=[59.2,70.3)$, MinutesSedentary$=[795,842)$, MinutesVeryActive$=[39.52]$</td>
<td>High</td>
<td>0.077</td>
<td>1</td>
<td>1.711</td>
</tr>
<tr>
<td>MinutesSedentary$=[795,842)$, MinutesVeryActive$=[39.52]$</td>
<td>High</td>
<td>0.062</td>
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TABLE II
PRODUCTIVITY RULES RANKED BY LIFT


