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Wearable data analysis, visualisation and recommendations on the go using android middleware

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Abstract Wearable technology comes with the promise of improving one's lifestyles thru data mining of their physiological condition. The potential to generate a change in daily or routine habits thru these devices leaves little doubt. Whilst the hardware capabilities of wearables have evolved rapidly, software apps that interpret and present the physiological data and make recommendations in a simple, clear and meaningful way have not followed a similar pattern of evolution. Existing fitness apps provide routinely some information to the wearer by mining personal data but the subsequent analysis is limited to supporting *ad hoc* personal goals. The information and recommendations presented are often either not entirely relevant or incomplete and often not easy to interpret by the wearer. The primary motivation behind this research is to address this wearable technology software challenge by developing a middleware mobile app that is supported by data analytics and machine learning to assist with interpretation of wearer data and with making of personal lifestyle improvement recommendations on the go which may then be used to feedback to the wearer's daily goals and activities. The secondary motivation is to correlate and compare with trends in the wearer's peer community.

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1 Introduction

Google's Verily Life Sciences have recently unveiled an ordinary looking health tracking "study watch" to unobtrusively and continuously collect physiological data from the wearer, such as their heart rate, electrocardiograms (ECG), movement data, their skin's electrical conductance as well as ambient light and sound. The Google watch does not currently allow the wearer to see their health data, only the date, time, and some instructions. The long-term vision of Verily is to unravel biomarkers through tracking thousands of healthy people especially when they fall ill. Although the watch features a processor that manages and encrypts its wearer's data and its software is updatable over-the-air, Verily is not currently marketing the watch as a medical device, for which they will need FDA approval, but as a clinical and observational tool for scalable collection of rich and complex data sets. The watch's battery lasts for up to a week without a charge and it stores "raw" data produced over the same amount of time, so it does not have to be synched as frequently as other watches. The inclusion of an ECG which Verily regards as their biggest technical novelty can reveal heart abnormalities. Such measurements are normally taken in hospitals with several stick-on electrodes but the Google watch picks up a lower-resolution signal from just two electrical contacts when the wearer grasps the metal bezel with their other hand. The watch is being deployed in a study in Europe whose aim is to track the progression of Parkinson's disease among patients diagnosed with the disease. Uninterrupted long-term sleep and heart readings are invaluable in monitoring the progression of Parkinson's and cannot be monitored in hospitals, especially the patients' sleep patterns. Verily argues that the watch's scope can be extended through the inclusion of additional sensors that will help generate additional bio-feedback thus shaping its place in the Internet of Things (IoT) landscape [8, 11, 12].

Having continuous and uninterrupted access to such personal data in real time may help with the diagnosis of underlying conditions on the go, as maybe the case with Google's watch, and making personal recommendations on life style improvements, otherwise, by identifying personal preferences and behaviour including food habits, sleep patterns, and daily activity schedules. It is widely acknowledged that all these devices can motivate individuals to change habits towards a better health or lifestyle. For instance, they are being considered in the workplace to monitor workers' activities and control schedules and as they hold consumer's health data, these devices are also a point of interest for physicians and health insurers [1, 10, 21].

Samsung, Fitbit, Apple and Sony have long joined the race in wearable technology hardware but according to Verily, the next but necessary stage in the evolution is the development of software algorithms that can "interpret" the wearer's raw data, thus making accurate diagnoses and personalised recommendations, where possible, often by comparing the wearer's data against the data of other wearers in the same peer group [3, 14]. As these devices cover a broad range of wearers of different ages, physical conditions and lifestyles, it is important that the presented information is as useful to all wearers as the wearable hardware with which it has been recorded. This would in turn inform the development of personalised immersive and alternative reality environments.

The focus of this paper is to address the wearable technology software challenge by developing such a personal immersive environment that collects, analyses and visualises personal wearer data mined with a wearable device and which integrates a machine learning approach to making personal recommendations for lifestyle improvements on the go in close consideration of trends in the wearer's peer community. These lifestyle improvement recommendations may then be used to feedback to the

Table 1 Issues with wearables

	Ethical/Legal	Economic	Social	Technological
Intellectual Property	√			
Data Protection	√			
Privacy	√			
Safety	√			
Regulation		√		
Innovation		√		
Price		√		
Choice		√		
Connectivity			√	
Integration			√	
Inclusion			√	
Networking			√	
Systems Interoperability				√
Technical Standards				√
Wireless Connectivity				√
Data Security				√
Application areas		√		√
Usability				√
Real-time				√

wearer's daily goals and activities. As access to Google watch's wearer data is currently restricted, the authors showcase their approach with a Samsung Gear Fit and Fitbit. The environment is developed as a mobile middleware app aimed at offering personal recommendations on the go for improving personal lifestyles. To show how this aim has been achieved, the rest of the paper is organised as follows: Section 2 presents a related research review, section 3 details the mobile apps developed, including our data analysis and machine learning approaches, and section 4 presents our experimentation. Section 5 concludes.
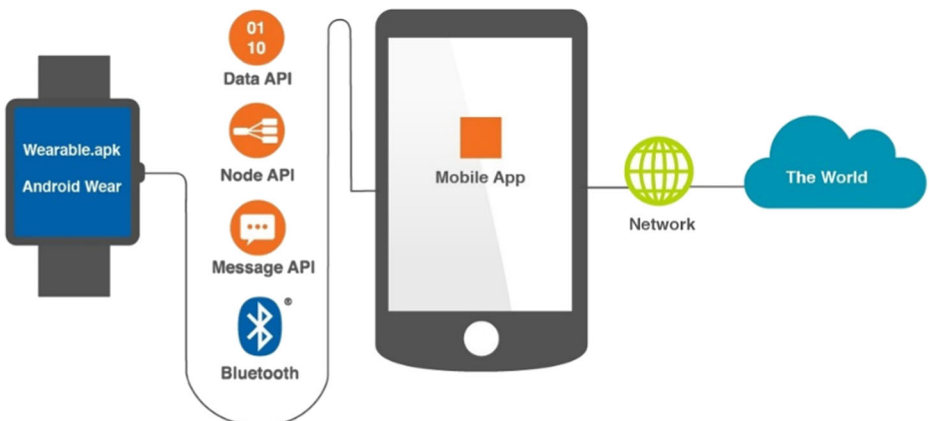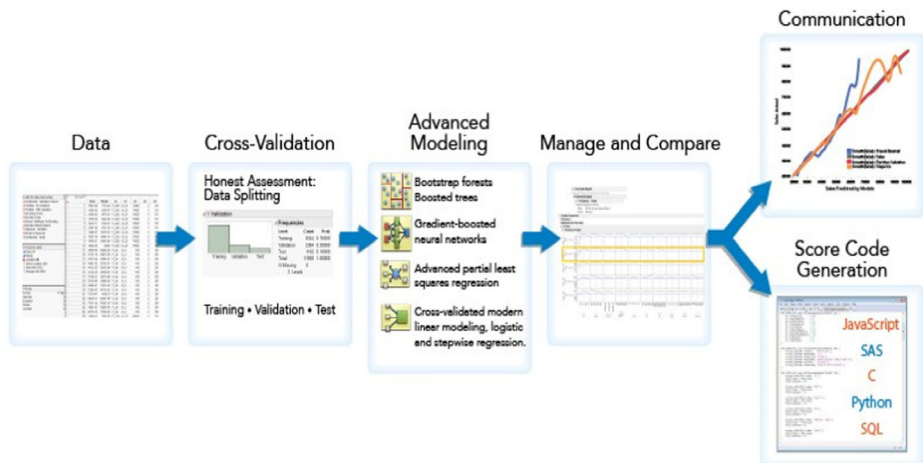

Fig. 1 Social connectivity [34]
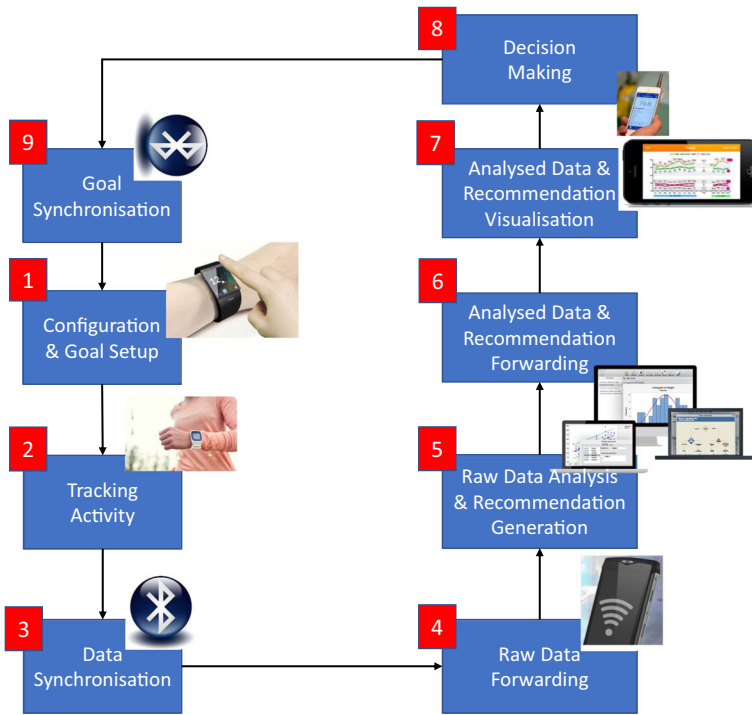
Fig. 2 A flowchart of wearable data analysis, visualisation and recommendation

2 Related research review

Table 1 shows the range of issues reported in literature and arising from our research review [1–14, 16, 18–27, 31–36]. The findings have been grouped under four categories, namely ethical/legal, economic, social and technological. However, the boundaries between these categories are fuzzy since discussion of these issues has been from various perspectives. This

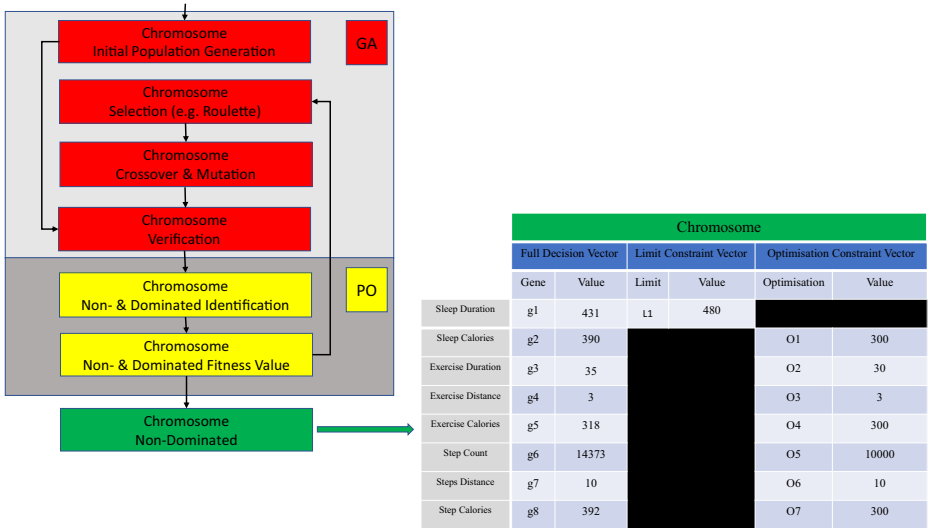**Fig. 3** A flowchart of comparative analysis during steps 5 and 6

	Chromosome					
	Full Decision Vector		Limit Constraint Vector		Optimisation Constraint Vector	
	Gene	Value	Limit	Value	Optimisation	Value
Sleep Duration	g1	431	L1	480		
Sleep Calories	g2	390			O1	300
Exercise Duration	g3	35			O2	30
Exercise Distance	g4	3			O3	3
Exercise Calories	g5	318			O4	300
Step Count	g6	14373			O5	10000
Steps Distance	g7	10			O6	10
Step Calories	g8	392			O7	300

Fig. 4 A flowchart of GA and PO deployment during steps 5 and 6 and a typical chromosome

**Fig. 5** FitNalyser opening screen
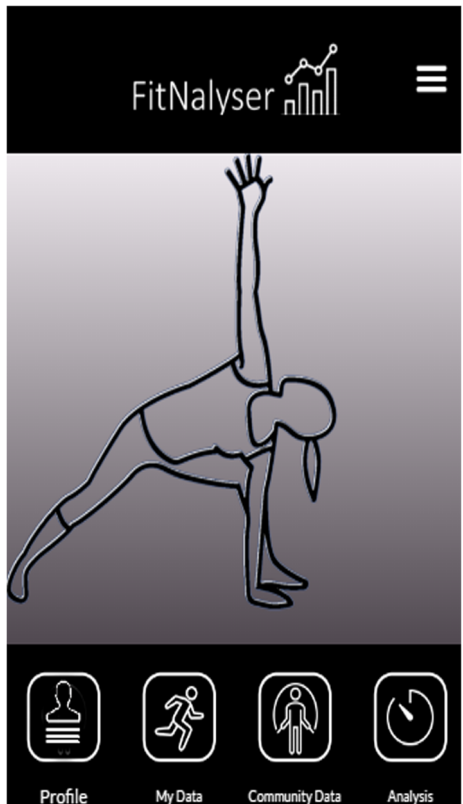
Fig. 6 FitNalyser Profile screen
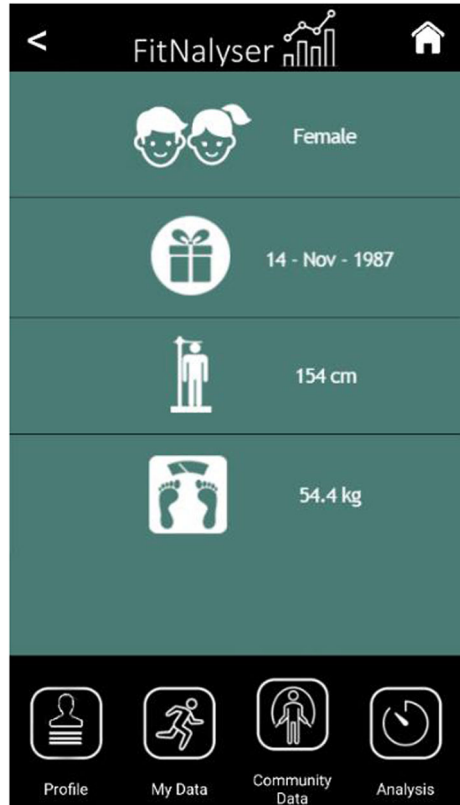
is the result of this subject area being very multidisciplinary in nature whereby contributions have been made from different fields.

Whilst the focus of our research review has been primarily software apps that support the wearer in their daily use of the wearables, which reportedly is now at the core of wearable software evolution, what has been reported so far in literature in relation to our objective are software apps that support and fine-tune the functionality of the wearable technology, e.g. energy consumption or display resolution.

An Argus Insights Report [2] argues that whilst wearable hardware has been improving to an evolving standard, the same cannot be said for wearable software apps that interpret the data such devices collect. The report suggests that a clear gap exists between devices and such software apps that may enhance an aspect of the wearer's lifestyle such as responsive learning or interactive gaming. Despite that, social connectivity through wearables has been on the rise where there is a common goal such as fitness or gaming. Figure 1 illustrates an Android wearable device linking up with a smartphone through Bluetooth and communicating with the cloud and other wearers who do the same.

Therefore, we have had to consider such software app developments in closely related subjects, i.e. for analysing and presenting data collected from single or multiple sensors like those that define the wearable technology functionality; for example, optical sensors such as those for heart rate monitoring through measurement

Fig. 7 FitNalyser My Data screen
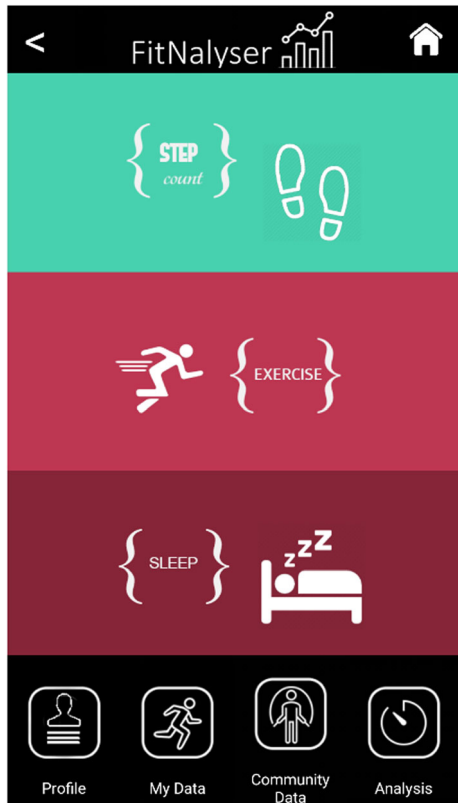
of blood flow changes, chemical sensors such as those for hydration monitoring through real-time measurement of sodium and potassium levels in body sweat, temperature sensors for monitoring the ambient temperature or impact sensors for monitoring vibration. Liu et al. [15] paint a landscape of human activity recognition sourced from past landscapes that includes sensor-based approaches that shed light on current progress which is still slow and not reaching far enough in satisfying the wearer needs.

Shoaib et al. [28] present an android smartphone app that collects data using a Samsung Galaxy S2 smartphone's accelerometer, gyroscope and magnetometer sensors to collect data on physical activities such as walking, running, sitting, standing, walking upstairs or downstairs and then analysing this data using WEKA's machine learning tool, with mixed success. The app typifies the approach most authors report, i.e. the use of one or more sensors to collect data and then correlate the data to one or more physical activities. Liu et al. [15] survey several approaches and apps that follow this approach to collect data and then use a variety of techniques to interpret the data such as Neural Nets, Bayesian Networks, Decision tables and trees, etc.

Several limitations are reported and arise with existing approaches and android apps that are deployed to support the wearer in revisiting their fitness goals, for example. Wearers often perform multiple activities at the same time or may change,
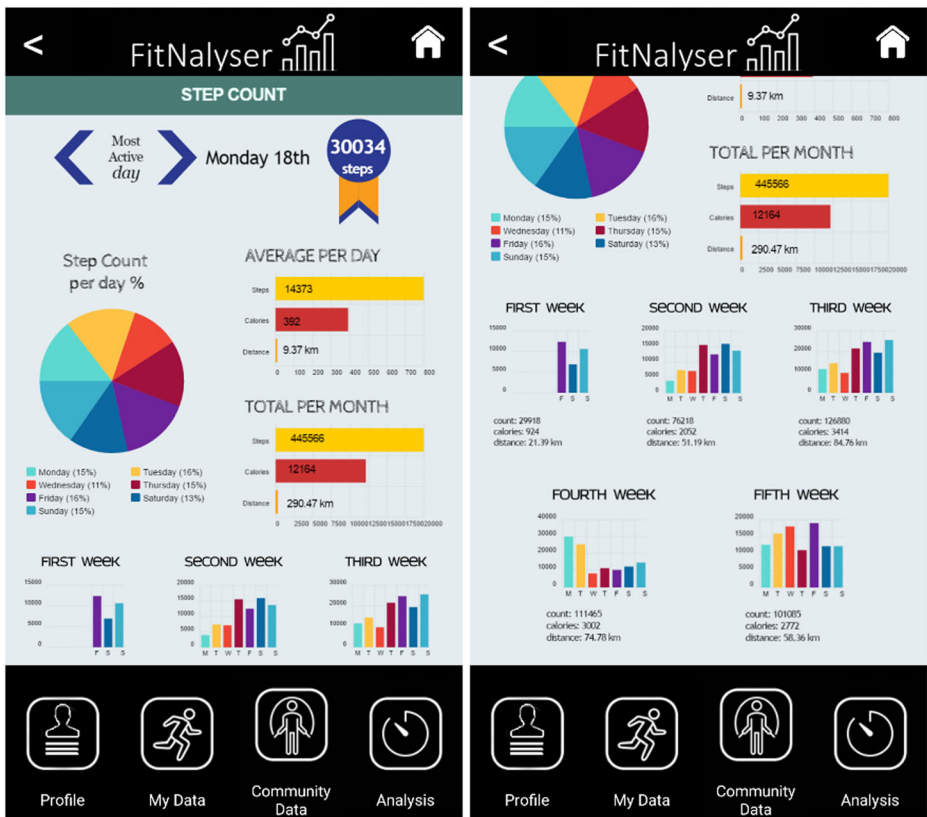
Fig. 8 FitNalyser step count screen

planned or unplanned, from one activity to another; for instance, part of a wearer's running course may involve going up or down a set of stairs. How is data correlated to each activity in such a case? As discussed earlier wearables are increasingly used as social connectivity tools, thus wearers often set their goals and compare their performance against that of their peer group. Current approaches and android apps only serve the wearer. How can wearer initial or revised fitness goals and performance data, for example, be set and compared to that of their peer group? Current approaches and android apps focus primarily on interpreting past performance and presenting the results to the wearer. How can past wearer and peer group performance be used to make on-the-go recommendations to the wearer? In the next section, we present an android app that addresses the above shortcomings.

3 Wearable data analysis, visualisation and recommendation

We have used Mobincube to develop two versions of the android middleware app for Samsung smartphones [17]. One version is entitled FitNalyser and the other Bru-Fit. We have integrated JMP PRO with MatLab's Genetic Algorithms (GA) and Pareto Optimality (PO) to analyse and
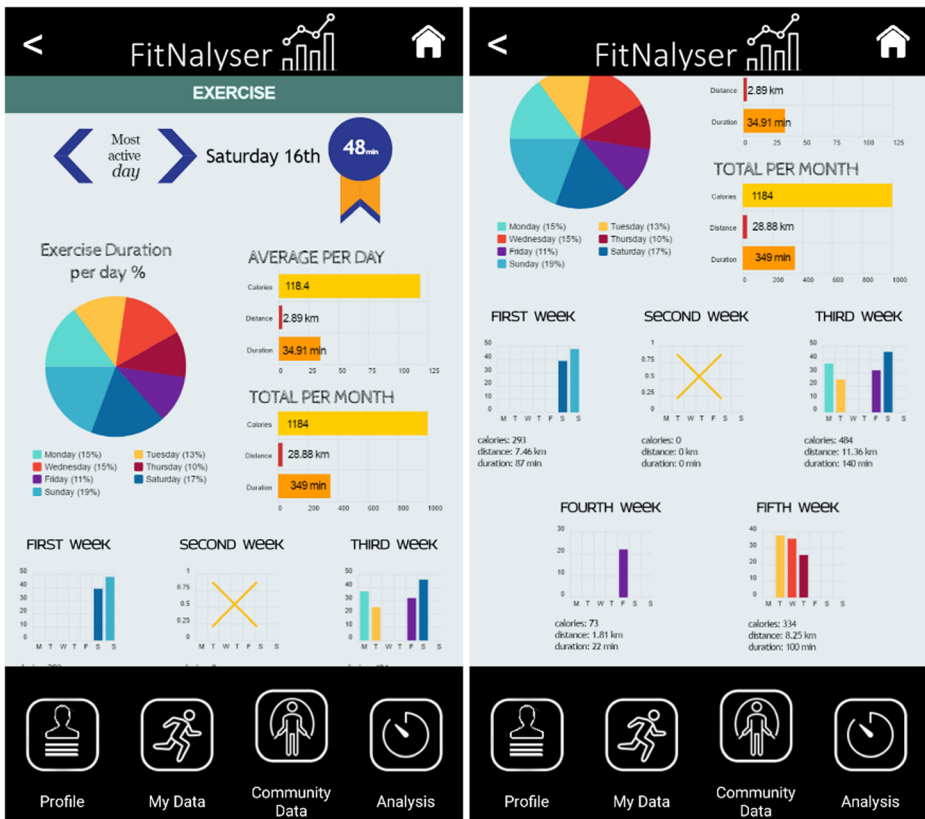
Fig. 9 FitNalyser exercise screen

compare the wearer's data to peer community data with the former and to use the result to generate recommendations that may support the wearer with monitoring their daily goals and activities with the latter.

Figure 2 shows a flowchart of the use of a wearable device, the analysis and visualisation of the wearer activity data it records and the recommendations generated using a machine learning technique to support the wearer with their monitoring of their daily goals and activities. The wearer configures their wearable and sets initial goals (1), the wearable sensors track the wearer's daily activities and record data (2), the wearable synchronises with a smart device to transfer the wearable data recorded (3), the raw data is forwarded by the smart phone to the wearable data server (4) from which it is retrieved and analysed in comparison to community data to generate personal recommendations (5), the results of the analysis and the recommendations are forwarded to the smart device (6) where they are visualised and offered to the wearer (7) so that they may assist them with monitoring their daily goals and activities (8). The smart phone synchronises with the wearable to auto-update any revised goals (9).

Iterating through steps 1 to 4, then 8 and 9 is the standard process with almost all wearable devices when paired with a smart phone. In our work, we introduce three additional steps, i.e. 5, 6 and 7, that address the shortcomings highlighted at the end of the previous section
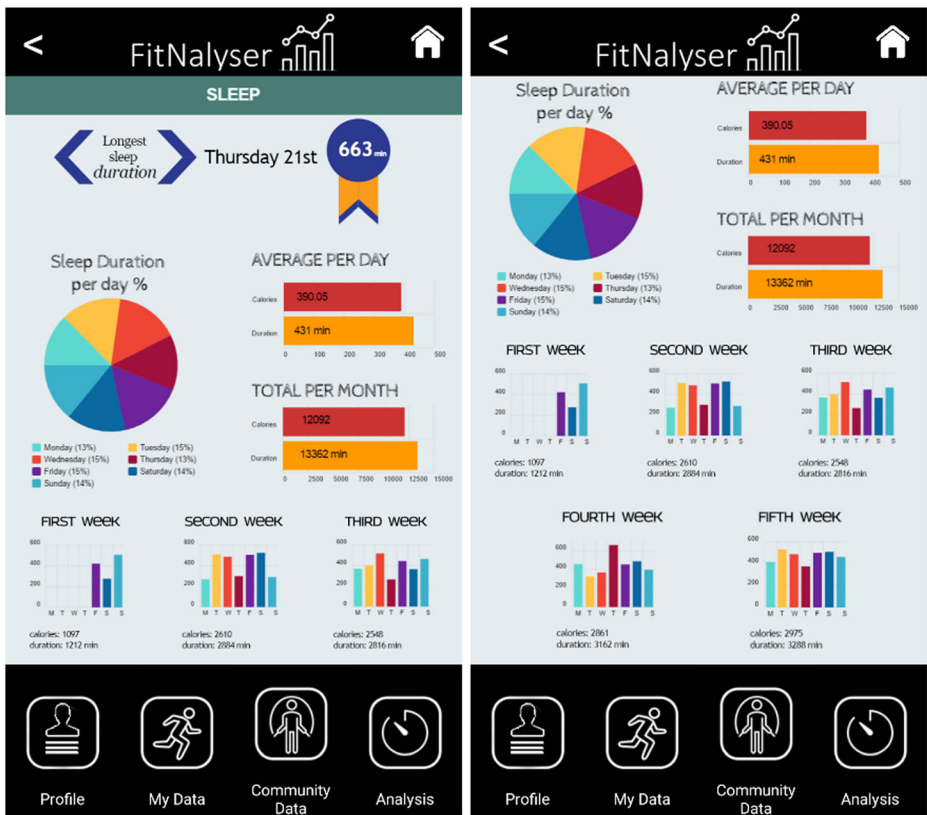
Fig. 10 FitNalyser sleep screen

and represent our novel contribution to research and development. JMP PRO and MatLab's GA and PO are deployed at steps 5 and 6, and either FitNalyser or Bru-Fit are deployed at step 7.

3.1 Steps 5 and 6: Comparative analysis and recommendation generation

Figure 3 shows a flowchart of the process of comparative analysis with JMP PRO during steps 5 and 6. JMP Pro has been selected for raw wearable data analysis and comparison to peer data for many reasons. First, it enables predictive modelling through the set of techniques it deploys, e.g. decision trees, bootstrap forest, Naive Bayes and neural networks. Stats emerge with these techniques, e.g. the average influence of additional hours of sleeping on calorie burning, residual variation of number of steps mid-week and at weekends, all of which help with model prediction accuracy even with missing or incomplete data. Second, it enables cross-validation through the set of techniques it uses, e.g. data partitioning or holdback. Cross-validation is not only invaluable when comparing wearer data to peer data but also building a predictive model that is not based on a single wearer sample which in turn avoids over-fitting. Third, it allows model comparison through common quality measures, e.g. R2, ROC, AUC, etc. This helps with selecting a model with the best goodness of fit, parsimony and cross-

Fig. 11 FitNalyser Community Data screen
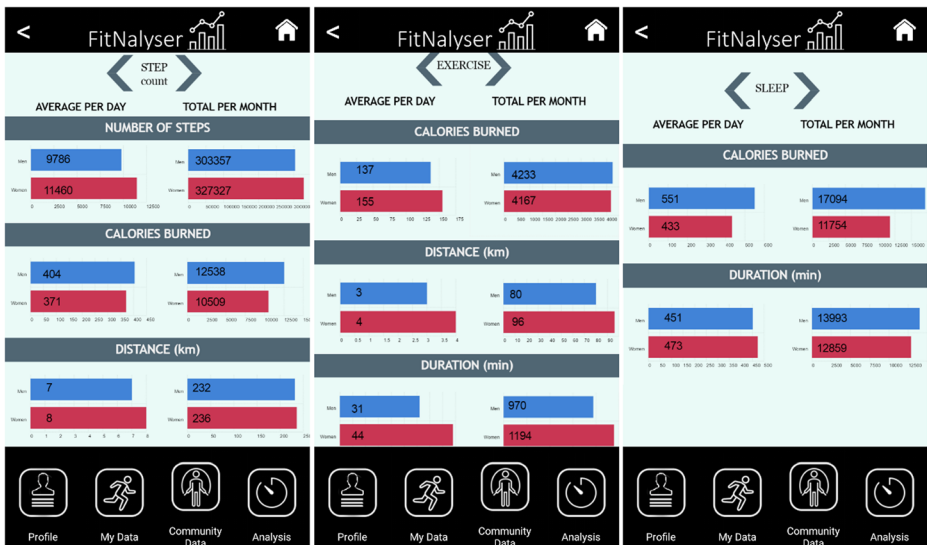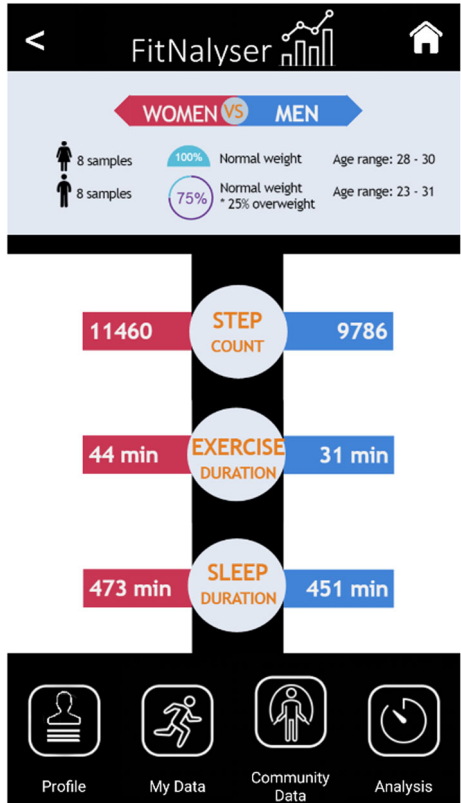
Fig. 12 FitNalyser Community Data stats for step count, exercise and sleep
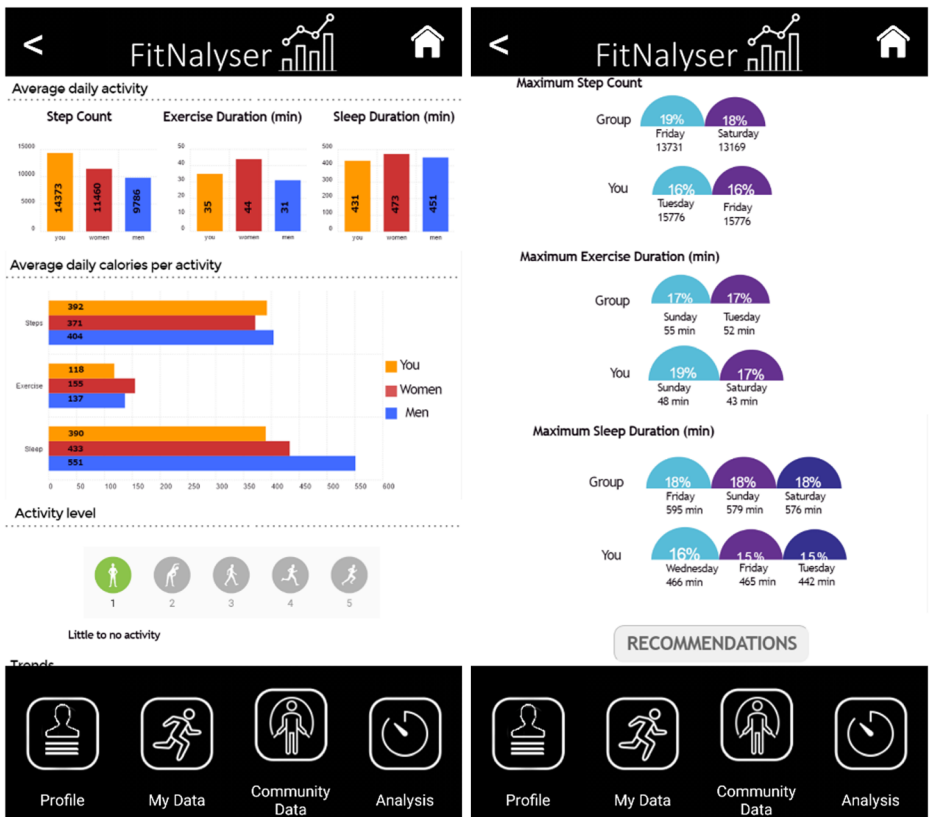
Fig. 13 FitNalyser Analysis screen

validation as input to the GA. Fourth, it uses generalized regression through a set of regularization techniques such as Ridge, Lasso, adaptive Lasso, Elastic Net, adaptive Elastic Net that help overcome the biases that arise with strongly correlated predictors, e.g. number of hours sleeping and calorie burning which may result in over-fitting. This approach helps with building a diverse predictive model that may include data with many outliers, or skewed data.

Figure 4 shows a flowchart of MatLab's GA and PO deployment during steps 5 and 6. Generating an optimal recommendation D_i for each wearer becomes a multi-optimisation problem (MOP) which seeks to optimise objectives $\cup_{d=1}^{k} O_d(D) \leq 0$ subject to limit constraints $\cup_{d=1}^{m} L_d(D) \leq 0$: $F(\overrightarrow{x}) = (f_1(\overrightarrow{x}) \ldots f_k(\overrightarrow{x}))$ where $\overrightarrow{x}$ is an n-dimensional decision variable vector $(\overrightarrow{x} = x_1, \ldots, x_n)$. The objectives and limit constraints are sourced from the best goodness of fit wearer model produced by JMP PRO in comparison to peer community data, e.g. steps per day, hours sleeping per night, hours exercising per day. Sofokleous and Angelides [29] suggest the use of GAs and Pareto Optimality (PO). The GA uses a fitness-based selection operator, such as roulette, to select chromosomes for reproduction from the evolved population and uses crossover and mutation to reproduce new offspring chromosomes. Once a termination criterion s met, the GA delivers one or more chromosomes as best-fit recommendations, D_i, that satisfy all limit constraints, e.g. min number of sleeping hours. The PO evaluates each
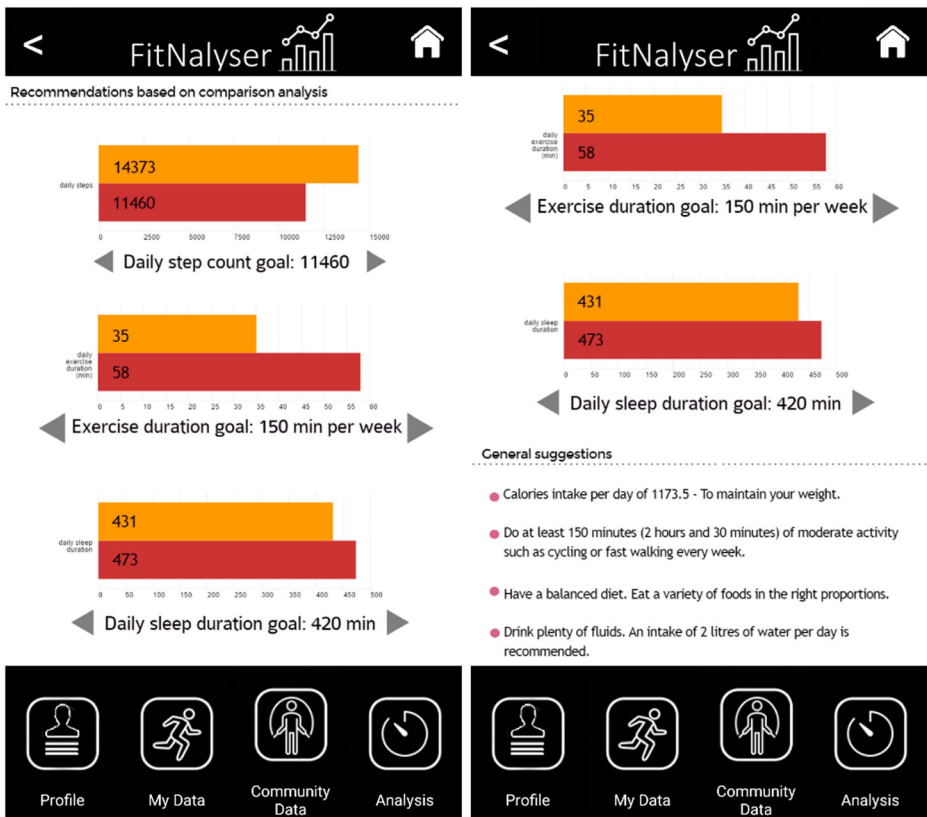
Fig. 14 FitNalyser Recommendations screen

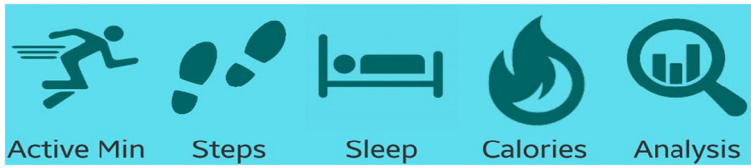**Fig. 15** Bru-Fit's top section of the opening screen

Fig. 16 Bru-Fit's bottom section of the opening screen

D_i with reference to optimisation objectives, O_i, e.g. max number of steps per day, to distinguish between dominated and non-dominated chromosomes and then assigns a strength value to each non-dominated chromosome that is proportional to the number of the dominated chromosomes it weakly dominates. Figure 4 also includes an example of a typical chromosome as a Full Decision Vector along with its Limit and Optimisation Constraints Vectors. The chromosome population (P) is expressed as $P = P_E \cup P_I$, where P_E and P_I contain the non-dominated and dominated chromosomes respectively. The strength value of a non-dominated C_i is expressed as $S(C_i) = \frac{|\{C_j | C_j \in P_I \& C_i \preceq C_j\}|}{|P_I| + 1}$, where $C_i \in P_E$. The PO then calculates a fitness value for each dominated chromosome, C_j, as the sum of the strength values of the non-dominated chromosomes that weakly dominate C_j, i.e. $F(C_j) = 1 + \sum_{i=1}^{|P_E|} \begin{cases} S(C_i) & , \text{if } C_i \preceq C_j \\ 0 & , \text{otherwise} \end{cases}$, where $C_i \in P_E$. A dominates

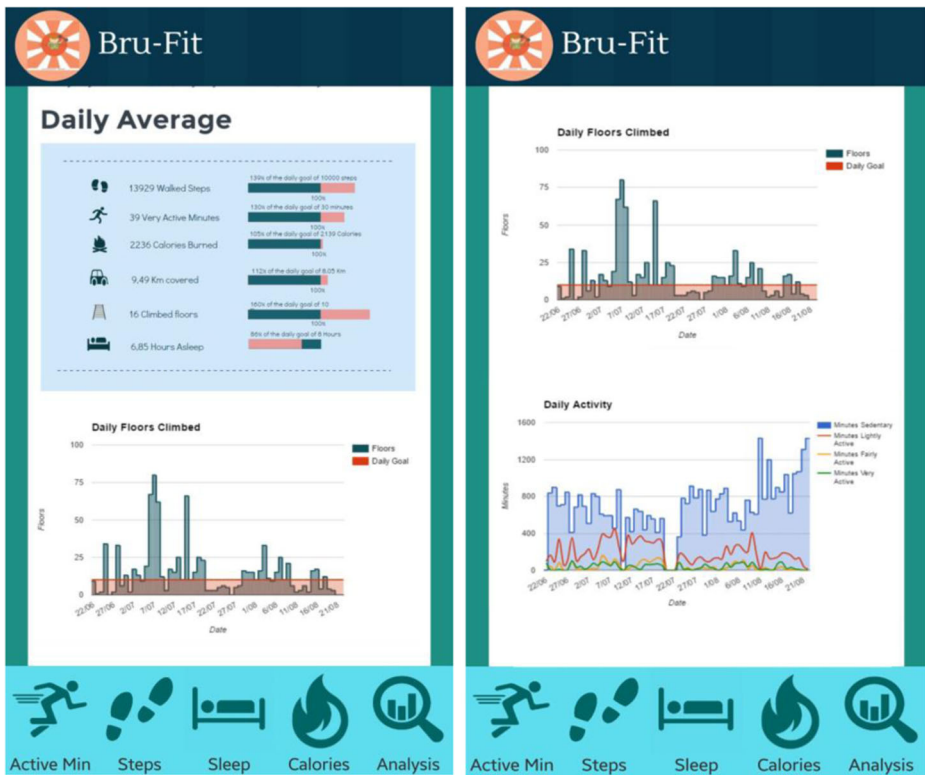**Fig. 17** Bru-Fit's general information screen

Fig. 18 Bru-Fit's Active Min screen

B, $A \prec B$, iff $O_i(A) \leq O_i(B)$, $\forall i = 1, \ldots, D$ and $O_i(A) < O_i(B)$ for some i and A weakly dominates B, $A \preceq B$, iff $O_i(A) \leq O_i(B)$, $\forall i = 1, \ldots, D$, where D is the number of optimisation constraints. A Pareto Front of optimal D_i (C_j) that satisfy: $f : P'_E = \{C_1, C_2, \ldots, C_n\} \longrightarrow C_j \in P'_E$ is produced where n is the number of chromosomes. Game theorists argue that the distribution of optimal solutions on a Pareto Front suggests the existence of a "best-fit" optimal recommendation D_i. Sofokleous and Angelides [30] calculates Euclidean Distances (ED) between each chromosome, i.e. a similarity measure between two chromosomes: $ED(C_j, C_i) = \sqrt{(O_1(C_j) - O_1(C_i))}^2 + \ldots + (O_m(C_j) - O_m(C_i))^2$, where $O_k(C_z)$ is the result of evaluation of O_k using chromosome C_z values. The closer C_j is to C_i, the more likely is that C_j will result in the same satisfaction as C_i. The fitness value of each chromosome is then re-calculated and the one with the highest $f(C_i)$ value is selected as the "best-fit" optimal recommendation D_i and recommended to the wearer:

$$f(C_i) = \left(10 + \sum_{C_j \in P'_E} \frac{UserRating}{1 + ED(C_j, C_i)} \right) / \left(1 + |P'_E| \right)$$
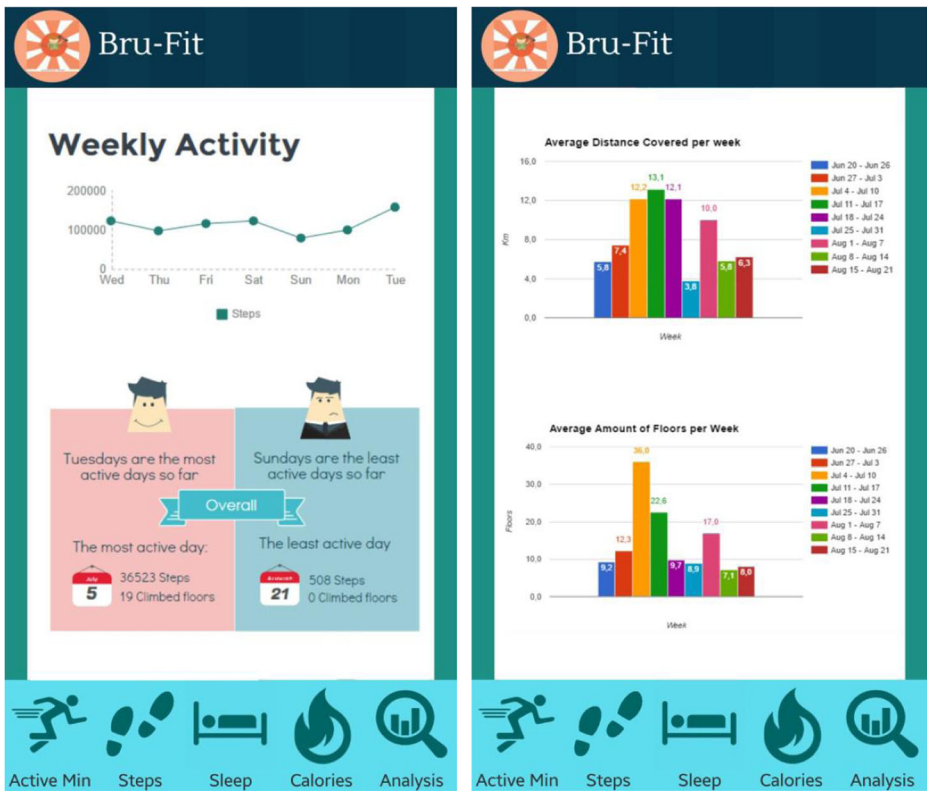
**Fig. 19** Bru-Fit's Active Min screen weekly average

The models produced by JMP PRO and the recommendations generated by the GA and PO are then forwarded to either FitNalyser or Bru-Fit for visualisation during step 7.

3.2 Step 7: FitNalyser

This android middleware app runs on a Samsung smartphone paired with a Samsung Gear Fit hybrid smartwatch and fitness tracker which may be worn 24/7 since it is an always-on activity tracker that measures "steps", "exercise", "sleep" and "heart rate". The 9-step process of Fig. 2 that includes FitNalyser at step 7 unfolds as follows:

1. Configuration and Goal Setup: The wearer populates their wearable with personal data, such as name, gender, age, weight, and height, to enable the device to collect data correctly and sets up their daily goals, e.g. number of steps, number of hours spent walking or sleeping.
2. Tracking Activity: The wearable's sensors track the wearer's daily activities and sleep patterns without inhibiting any of their senses.

Fig. 20 Bru-Fit's Active Min screen monthly average
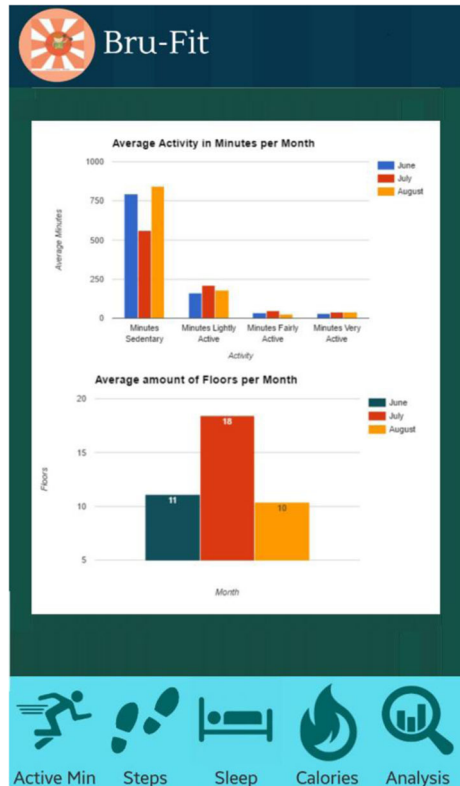
3. Data Synchronisation: The wearable establishes a Bluetooth connection to, and synchronizes with, the smartphone to transfer collected data.

4. Raw Data Forwarding: Data Viewer, a third-party software tool running on the smartphone, receives the dataset and packages this for transfer to a laptop via the tracker's cloud servers.

5. Raw Data Analysis and Recommendation Generation: JMP PRO performs generalised regression analysis of the wearer dataset in comparison to the peer community dataset and produces a model that is used by the GA and PO to generate recommendations.

6. Analysed Data and Recommendation Forwarding: The laptop transfers the model produced by JMP PRO and the recommendations generated by the GA and PO back to the smartphone via the tracker's cloud servers.

7. Analysed Data and Recommendation Visualisation: The analysed data model and recommendations are visualised on FitNalyser to support the wearer with monitoring their daily goals and activities.

8. Decision Making: The wearer reconsiders his current daily goals and activities, and may set up new activity goals, e.g. increase the number of hours spent sleeping, reduce the number of hours spent walking.

9. Goal Synchronisation: The smart phone synchronises with the wearable to auto-update any revised goals.
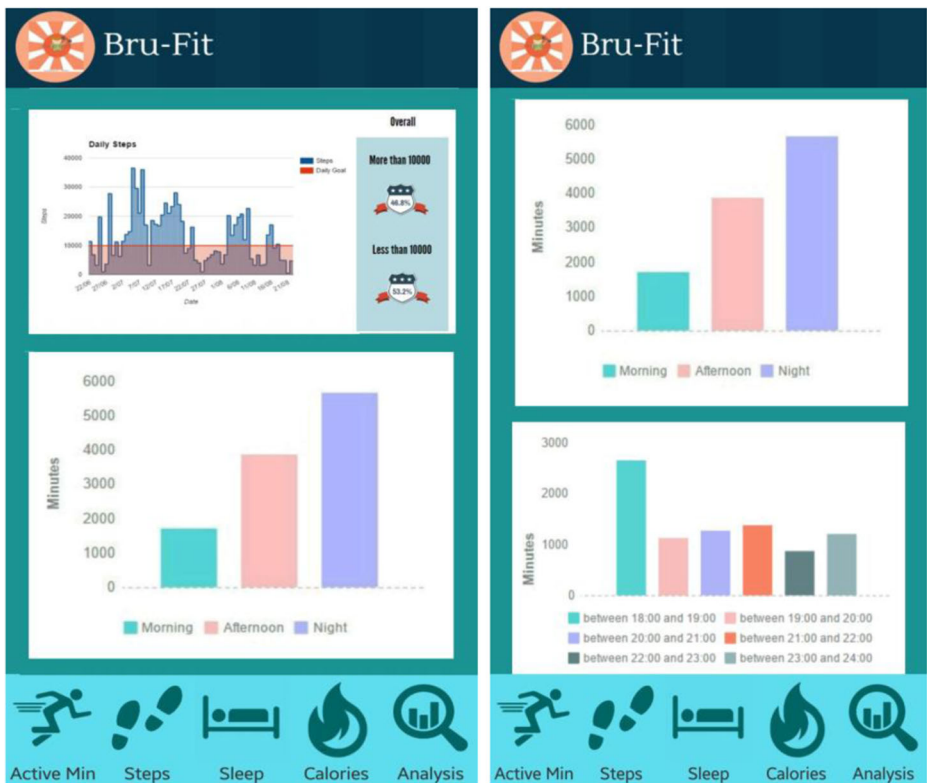
Fig. 21 Bru-Fit's Steps screen daily

Figures 5 through to 14 showcase the FitNalyser android app at step 7. Figure 5 depicts the opening screen of the mobile app which has been divided into 4 parts: profile, my data, community data and analysis. Figure 6 shows the wearer profile following configuration: Gender, date of birth, weight and height. Figure 7 shows My Data screen which offers the choices of step count, exercise or sleep to the wearer. On Fig. 8 the step count performance is visualised, i.e. the daily average of number of steps, burned calories and daily distance and the monthly total of number of steps, burned calories and distance following tracking. Similarly, on Fig. 9 the exercise performance is visualised, i.e. the daily average of burned calories, duration, and distance as well as the monthly totals. Likewise, on Fig. 10 the nightly and monthly sleep average is visualised. Figure 11 mirrors the choices on offer on My Data screen for Community Data but in addition it reveals the number and age range of wearers, differentiating between males and females, and their weight. On Fig. 12 the daily averages and monthly totals for Community Data for both genders are visualised. Figure 13 relays personal against community performance data following analysis wearer own data and comparison against community data, with a gender bias. This helps develop personal and community fitness trends in relation to all activities. On this screen, the wearer may choose to consider recommendations generated by the GA and GO during step 5. On Fig. 14 recommendations are visualised in relation to diet, hydration and excercising. The wearer may use these recommendations to review current daily goals and activities and set up new ones.

Fig. 22 Bru-Fit's Steps screen weekly and monthly
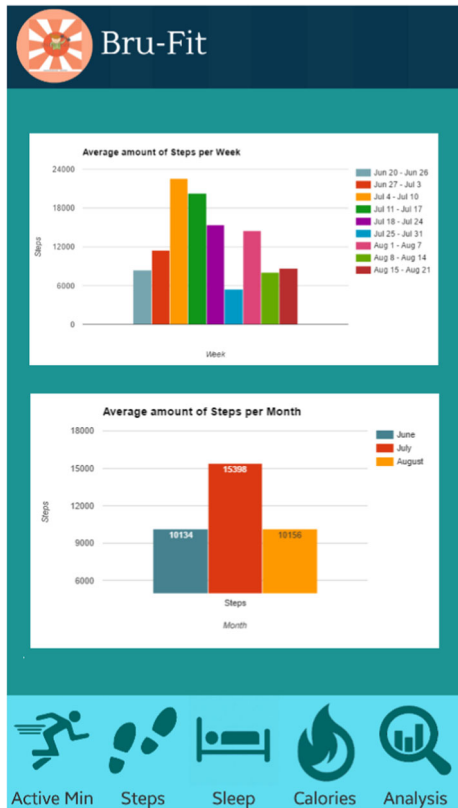
3.3 Step 7: Bru-fit

This android middleware app runs on a Samsung smartphone paired with a Fitbit® Surge hybrid smartwatch and fitness tracker that may be worn 24/7 as it is an always-on activity tracker that measures "steps", "exercise", "sleep" and "heart rate". Its sensors include GPS, 3-axis accelerometer, 3-axis gyroscope, digital compass, optical heart rate monitor, altimeter, ambient light sensor and vibration motor. The 9-step process of Fig. 2 that includes BruFit at step 7 unfolds as follows:

1-3. *Configuration and Goal Setup, Tracking Activity, Data Synchronisation: as with FitNalyser.*
4.   Raw Data Forwarding: A Fitbit open script executes the transfer of the raw dataset to a laptop via Fitbit's cloud servers.
5.   *Raw Data Analysis and Recommendation Generation: as with FitNalyser.*
6.   Analysed Data and Recommendation Forwarding: A Fitbit open script executes the transfer of the models produced by JMP PRO and the recommendations generated by the GA and PO back to the smartphone via Fitbit's servers.
7-9. *Analysed Data and Recommendation Visualisation, Decision Making, Goal Synchronisation: as with FitNalyser.*

Fig. 23 Bru-Fit's Sleep screen daily

Figures 15 through to 29 showcase the Bru-Fit android app at step 7. Figure 15 shows the top section of the opening screen of BruFit. Figure 16 shows the bottom section of the opening screen of BruFit, which has been divided into 5 parts: Active Min, Steps, Sleep, Calories, Analysis. Figure 17 gives an example of the general information that may be visualised on request. It shows the wearer's profile which includes their activity level and the daily goals set following configuration and goal setup. The wearer may revisit these goals and set up new goals after considering the recommendation. More detailed stats are available in the Activity Frequency section which shows personal bests in relation to Steps, Very Active Minutes, Calories, km covered, Floors, and Hours Asleep. Figure 18 shows the Active Minutes screen which includes a daily average of steps, active minutes, calories, km covered, floors, and hours asleep and a comparison to the daily goals. Two detailed graphs show floor climbing and daily activity during the reporting period. Figure 19 reports the weekly activity and averages for floor climbing and distance whereas Fig. 20 reports the average monthly activity with emphasis on floor climbing. Figure 21 shows the Steps screen on which it compares the daily steps to the daily goal as well as a daily and hourly distribution of steps whereas Fig. 22 reports the weekly and monthly distribution of steps. Figure 23 shows the Sleep screen and reports daily sleep patterns and efficiency, actual sleep time, bed and rise time whereas Fig. 24 reports

Fig. 24 Bru-Fit's Sleep screen weekly and monthly

the weekly and monthly sleep data. Figure 25 shows the Calories screen that details daily, weekly and monthly calories spent whereas Fig. 26 visualises a comparison between personal and community data with a gender bias on calories spent using bar and line graphs and boxplots. Likewise, Figs. 27 and 28 visualise comparisons between personal and community data, also with a gender bias, in relation to sleep data and steps respectively. Figure 29 shows Bru-Fit's Recommendations screen whose content is generated by the GA and GO during step 5. This screen visualises recommendations in relation to sleep or lack of it, bed and rise times, calorific intake and spent, and activity or lack of it. The wearer may consider these recommendations to revisit current daily goals and activities and set up new ones.

4 Validation: a month in the process

This section presents the application of the process on Fig. 2 over the period of one month with each of the two applications that we have developed. The purpose of this is to validate our approach and, in particular, the novelty in steps 5, 6 and 7.

Fig. 25 Bru-Fit's Clories screen daily, weekly and monthly

4.1 FitNalyser

At **Step 1**, the wearer configures their wearable and sets their initial goals of daily step count, exercise and sleep. During **Step 2**, the Samsung Gear Fit tracks the daily step count, exercise and sleep durations and monitors the heart rate without inhibiting any of the wearer's senses. At **Step 3**, the wearable synchronizes with the smartphone using a Bluetooth connection and transfers the daily dataset to the Samsung smartphone. During **Step 4**, Data viewer which has been installed on the smartphone, receives the dataset, packages that as a cvs file and forwards this file via the tracker's cloud servers to a laptop that runs JMP PRO and the GA with PO. Table 2 shows a screenshot of the raw data file on step count. Data collected include start and end time, calories and distance.

During **Step 5**, once both the personal daily and the community datasets have been received on the laptop, JMP PRO is used first to analyse and compare the personal against the public community dataset and build a general regression model. The first calculation made is the Body Mass Index (BMI) which uses measures of weight and height to determine whether the wearer is under, normal or overweight. This will inform the values of the Limit and Optimisation Constraint Vectors. This is followed by the Basal Metabolic Rate (BMR) which estimates how many calories are spent even without any activity during
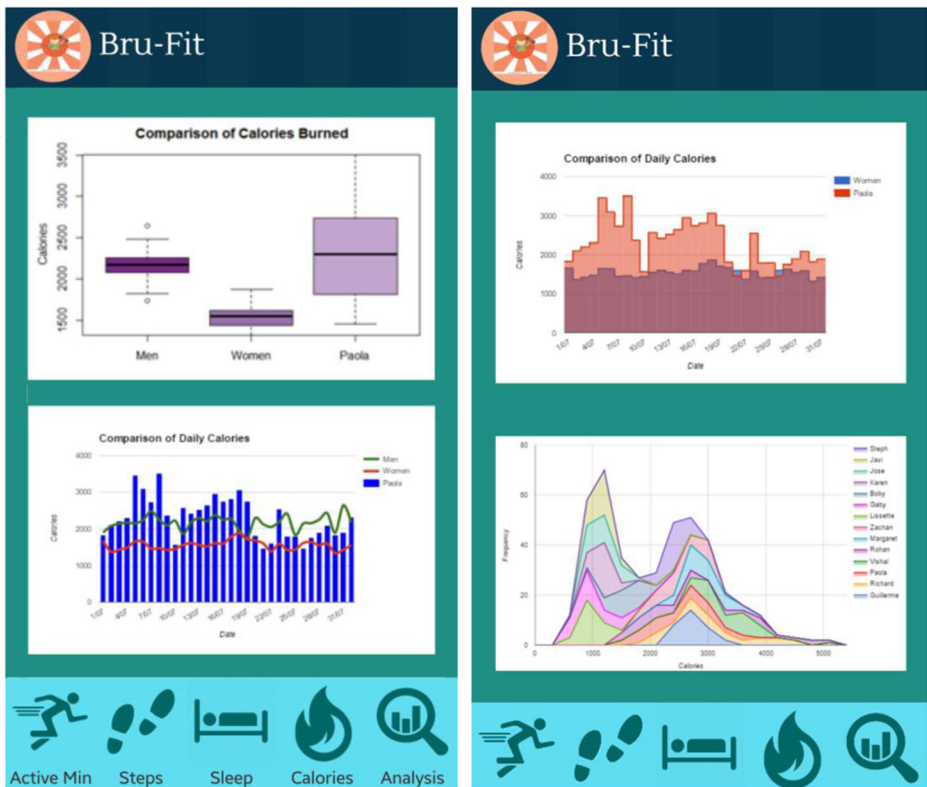
Fig. 26 Bru-Fit's Analysis screen comparing personal to community data in relation to calories

a 24-h period. This represents the minimum amount of energy required to keep the body functioning. The Harris-Benedict and Mifflin equations are commonly used to calculate BMR because of their accuracy. The BMR for men differs to that of women mostly due to their body weight:

For men: $(10 \times weight) + (6.25 \times height) - (5 \times age) + 5$.

For women: $(10 \times weight) + (6.25 \times height) - (5 \times age) - 161$

Table 3 gives the BMI and BMR calculated using parameters extracted from the personal dataset. These values are carried forward to the comparative analysis stage.

In addition to the BMI and BMR calculation, calculation of the calories burned during all measured activities with the wearable, i.e. walking, exercising, and sleeping are presented on Fig. 30. Figure 30 reveals that at the peak of walking the number of calories burned are less than the calculated BMR since the amount of energy required to support vital body functions is significantly higher.

A sample of a monthly personal dataset is presented on Table 4. The figure shows the total values of the variables relating to the three measured activities and their daily average. Moreover, a detailed distribution for each day of the week, regarding the main activities is shown on Table 5 which reveals the daily effort on a weekly basis with Tuesdays and Fridays peaking at 16%. Exercise is frequently occurring more on Sundays at 20% and sleep duration is at its peak on Wednesdays with 16%.

Fig. 27 Bru-Fit's Analysis screen comparing personal to community data in relation to sleep

Figure 31 reveals that when the number of the calories from all activities are added together, Tuesdays and Fridays are the days during which most calories are burned; this resembles the step count distribution. The community dataset has been compiled from 16 different wearers, 8 women and 8 men between the ages of 23 and 31 and it comprise of both qualitative and quantitative data: height (cm), weight (kg), age, gender, step_count, step_calories, steps_distance (km), exercise_calories, exercise_distance (km), exercise_duration (min), sleep_calories and sleep_duration (min). Table 6 shows the BMI and BMR of each wearer.

Figures 32 and 33 present the community's monthly distribution of spent calories during the measured activities with a gender bias. The two figures reveal a similar pattern for males and females. The range of calories spent whilst waking or sleeping is higher than whilst exercising with the maximum calories burned by women being around 16,000 whilst for men 20,000. The number of calories burned whilst sleeping is higher than daily exercising or walking because sleep duration does not vary as much as daily walking and exercising do as Fig. 34 shows. Figure 35 reveals that males spend more calories than females whilst sleeping and walking but less whilst exercising.

Fig. 28 Bru-Fit's Analysis screen comparing personal to community data in relation to steps

Figures 36, 37, 38, 39, 40, 41, 42 and 43 present detailed data analytics produced by JMP PRO. Figure 36 shows the daily mean for walking being 10,622.917 and reaching a maximum of 45,408 and dropping to a minimum of 308. Figure 37 presents the daily mean of calories spent during walking being 387.89 and reaching a maximum value of 1530 and dropping to a minimum of 11. Figure 38 illustrates the daily mean for distance covered ranging between a maximum of 34.5 and a minimum of 0.25. The boxplots indicate that there may be upper or lower limit outliers and the last minimum might be one of these. All three graphs show a positive skewness distribution, which indicate that the lower limits for steps, calories, and distance is higher than the higher limits. The results show that most datasets report between 5000 and 15,000 steps daily. Thus, the number of calories spent fluctuate between 200 and 600. On Fig. 39 the distribution is slightly flatter than a standard normal whereas Figs. 40 and 41 show kurtosis values higher than 3 which indicate a high number of outliers. This number of outliers is a consequence of either forgetting to register the daily exercise activity or not exercising. Figure 42 shows a negative kurtosis of −0.14 indicating a flatter distribution with only one outlier and a low skewness of 0.26 making it symmetrical than the others. Calories burned whilst sleeping are directly proportional to the wearer's weight, 50 kg to 79 kg. Thus, the distribution is most likely normal. Figure 43

Fig. 29 Bru-fit's
Recommendations screen

shows a negative skewness with a high kurtosis value since sleep duration does not follow the expected pattern.

Correlational analyses of the walking, exercising and sleeping dataset variables are presented on Figs. 44, 45 and 46. Whilst with exercising the correlation is similar to walking, with sleeping the correlation is not as high since the sleeping duration does not normally have a specific pattern, as wearers who exercise more daily are normally expected to sleep for longer periods. However, this is not always the case because a wearer may either have developed a regular sleeping pattern regardless or are unable to sleep for the required amount of time. Table 7 presents a full table of correlations between each variable of the dataset.

Table 8 presents a summary of daily activity over the period of one week. For instance, step counts usually rises at weekends whereas exercising rises mid-week and on Sundays and average sleep duration is higher at weekends in comparison to weekdays with 3 additional hours of sleep. The highest daily calorie consumption seems to take place on Fridays as Fig. 47 shows.

Figures 48, 49 and 50 map the personal against the community dataset. Figure 48 reveals that the monthly personal step count is higher than the community's average for females whereas Figs. 49 and 50 reveal that personal exercise and sleep periods are lower. Figure 51 provides a comparison of the calories expended for the monitored activities and it reveals that the calories expended reflects either the effort and or the activity duration.

Table 2 Step count's cvs data file

com.samsung.health.step_count

time_offset	end_time	speed	pkg_name	start_time	sample count	calories	distance	datauuid	deviceuuid	update_time	create_time
3600000	6/17/16 23:20	1.0366666	com.sec.android.app.shealth	6/17/16 23:19	14	0.51	07.81	c597e372-5b2	n651IFUG7o	6/17/16 23:19	6/17/16 23:19
3600000	6/17/16 23:26	2.4166667	com.sec.android.app.shealth	6/17/16 23:25	16	3.09	11.67	4a104a25-457	n651IFUG7o	6/17/16 23:30	6/17/16 23:30
3600000	6/17/16 23:28	5.0833335	com.sec.android.app.shealth	6/17/16 23:27	27	1.14	31.01	edee5f62-265	n651IFUG7o	6/17/16 23:30	6/17/16 23:30
3600000	6/17/16 23:29	2.9166667	com.sec.android.app.shealth	6/17/16 23:28	35	1.24	33.51	4a2d4896-5c2	n651IFUG7o	6/17/16 23:30	6/17/16 23:30
3600000	6/17/16 23:30	3.9722223	com.sec.android.app.shealth	6/17/16 23:29	23	0.85	23.11	1a47aeef-179	n651IFUG7o	6/17/16 23:30	6/17/16 23:30
3600000	6/17/16 23:31	1.9298451	com.sec.android.app.shealth	6/17/16 23:30	30	1.0099999	24.70	89f9a721-807	n651IFUG7o	6/17/16 23:30	6/17/16 23:30
3600000	6/17/16 23:32	2.1912923	com.sec.android.app.shealth	6/17/16 23:31	19	0.5899999	16.90	a5ec49fd-ba4	n651IFUG7o	6/17/16 23:31	6/17/16 23:31
3600000	6/17/16 23:34	2.8055556	com.sec.android.app.shealth	6/17/16 23:33	6	0.28	06.13	a583f27e-a49	n651IFUG7o	6/17/16 23:33	6/17/16 23:33
3600000	6/17/16 23:35	1.4919225	com.sec.android.app.shealth	6/17/16 23:34	10	0.29	07.38	777c3953-a54	n651IFUG7o	6/17/16 23:34	6/17/16 23:34
3600000	6/17/16 23:36	5.4722223	com.sec.android.app.shealth	6/17/16 23:35	6	0.93	08.10	b675040f-aa2	n651IFUG7o	6/17/16 23:37	6/17/16 23:37
3600000	6/17/16 23:38	3.2222223	com.sec.android.app.shealth	6/17/16 23:37	25	1.85	27.44	99439287-0d1	n651IFUG7o	6/17/16 23:37	6/17/16 23:37
3600000	6/17/16 23:40	1.3333334	com.sec.android.app.shealth	6/17/16 23:39	17	0.58	11.38	7340ab3a-381	n651IFUG7o	6/17/16 23:42	6/17/16 23:42
3600000	6/17/16 23:45	2.5555556	com.sec.android.app.shealth	6/17/16 23:44	54	3.27	48.34	1be95e90-e23	n651IFUG7o	6/17/16 23:55	6/17/16 23:55
3600000	6/17/16 23:46	5.888886	com.sec.android.app.shealth	6/17/16 23:45	8	0.66	11.71	b75e2467-547	n651IFUG7o	6/17/16 23:55	6/17/16 23:55
3600000	6/17/16 23:47	2.1388888	com.sec.android.app.shealth	6/17/16 23:46	38	1.52	34.56	70e3f7b9-8d2	n651IFUG7o	6/17/16 23:55	6/17/16 23:55
3600000	6/17/16 23:48	2.9444444	com.sec.android.app.shealth	6/17/16 23:47	18	0.61	17.74	37da7c16-002	n651IFUG7o	6/17/16 23:55	6/17/16 23:55
3600000	6/17/16 23:49	5.0555553	com.sec.android.app.shealth	6/17/16 23:48	9	1.08	12.95	abb5b8dc-571	n651IFUG7o	6/17/16 23:55	6/17/16 23:55
3600000	6/17/16 23:50	3.0277777	com.sec.android.app.shealth	6/17/16 23:49	23	0.7	20.99	259bb8bd-034	n651IFUG7o	6/17/16 23:55	6/17/16 23:55
3600000	6/17/16 23:51	3.1111112	com.sec.android.app.shealth	6/17/16 23:50	47	1.76	46.13	008c5fe1-068	n651IFUG7o	6/17/16 23:55	6/17/16 23:55
3600000	6/17/16 23:52	2.75	com.sec.android.app.shealth	6/17/16 23:51	32	1.22	30.51	a691ebd0-293	n651IFUG7o	6/17/16 23:55	6/17/16 23:55

Table 3 Personal BMI and BMR calculation

Height	Weight	Age	Gender	BMI	BMR
154	54.4	28	female	22.94	1205.5
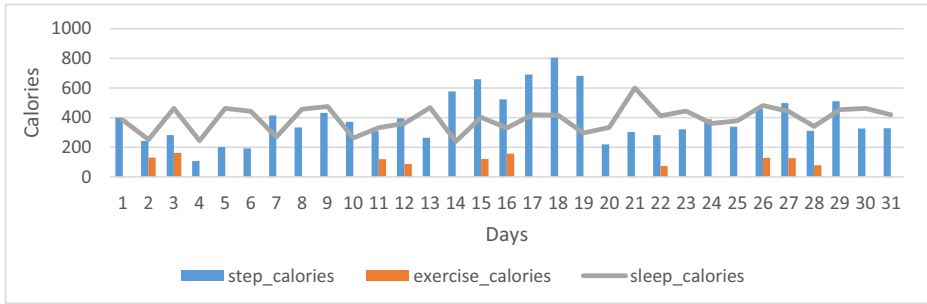
Fig. 30 Personal monthly distribution of spent calories during the measured activities

**Table 4** Personal monthly and average daily stats

	Step count	Step calories	Steps distance	Exercise calories	Exercise distance	Exercise duration	Sleep calories	Sleep duration
Per month	445566	12164	290.47	1184	28.88	349	12092	13362
Daily Ave	14373.10	392	9.37	118.40	2.89	34.91	390.05	431.03

Table 5 Personal daily summary on a weekly basis

|	Step Count	Step calories	Exercise calories	Exercise duration	Sleep calories	Sleep duration
Monday	14547	390	120	37	342	378
Tuesday	15776	434	108	31	400	442
Wednesday	10731	294	127	36	421	466
Thursday	14834	401	79	26	362	401
Friday	15771	437	97	27	421	465
Saturday	13305	369	143	43	392	433
Sunday	15328	412	163	48	384	425

Fig. 31 Personal weekly pie of
calories spent
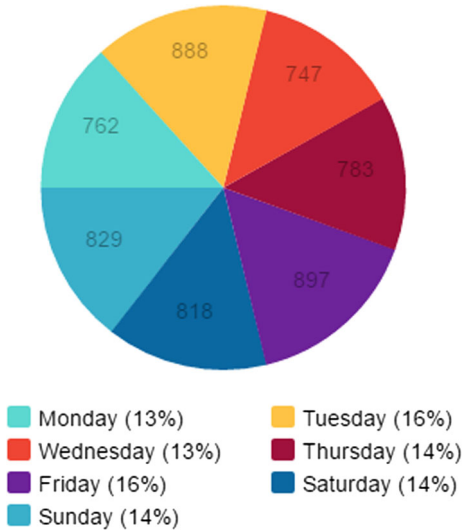
Table 6 Community BMI and BMR

Wearer	Height	Weight	Age	Gender	BMI	BMR
1	154	55	28	female	23.19	1211.5
2	159	50	28	female	19.78	1192.75
3	154	55	28	female	23.19	1211.5
4	160	53	30	female	20.70	1219
5	166	60	29	female	21.77	1331.5
6	155	55	28	female	22.89	1217.75
7	160	57	30	female	22.27	1259
8	157	56	29	female	22.72	1235.25
9	177	62	29	male	19.79	1586.25
10	178	80	31	male	25.25	1762.5
11	182	80	28	male	23.89	1808.75
12	180	79	28	male	24.38	1780
13	170	70	23	male	24.15	1802.5
14	174	70.3	30	male	23.22	1645.5
15	176	79	31	male	25.50	1740
16	169	76	30	male	26.61	1671.25
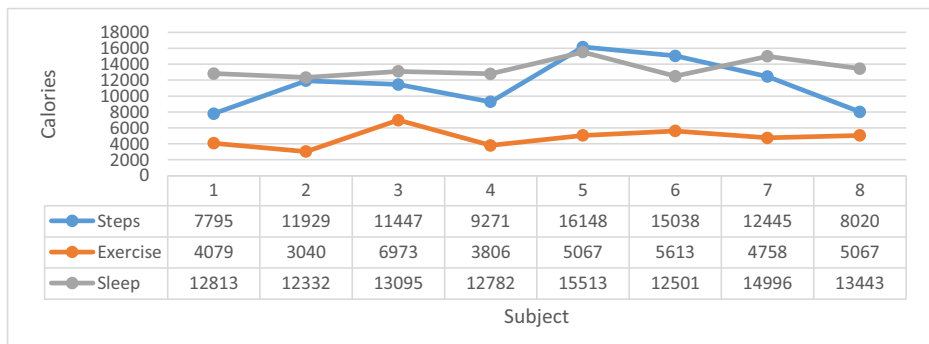
Fig. 32 Community monthly distribution of spent calories during the measured activities for females
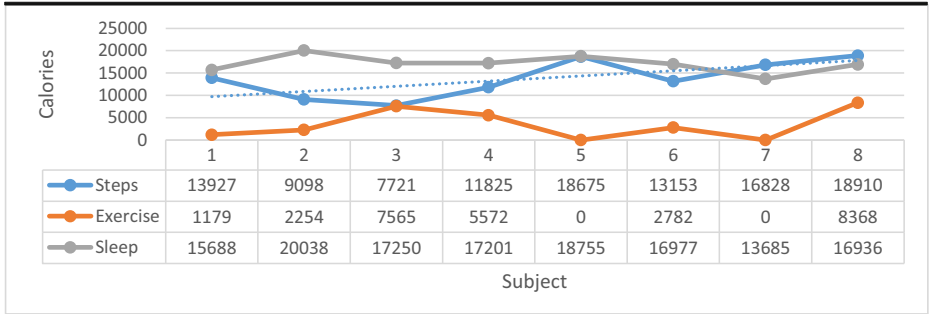
Fig. 33 Community monthly distribution of spent calories during the measured activities for males
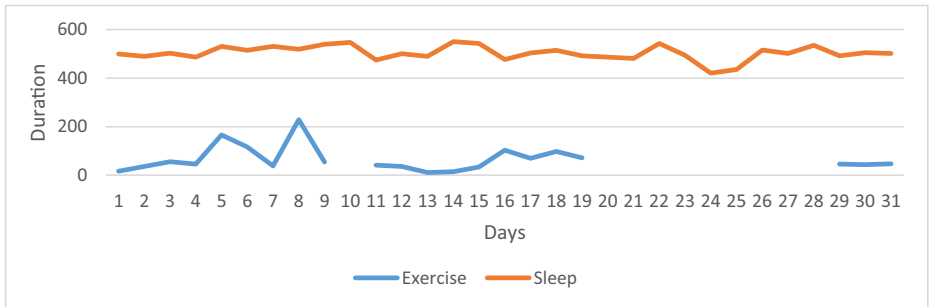

Fig. 34 Community monthly duration of exercising and sleep for women
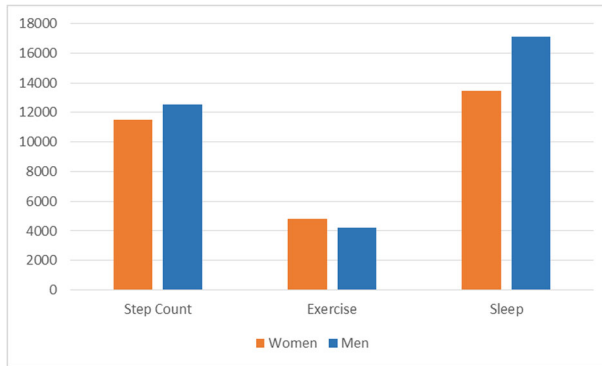

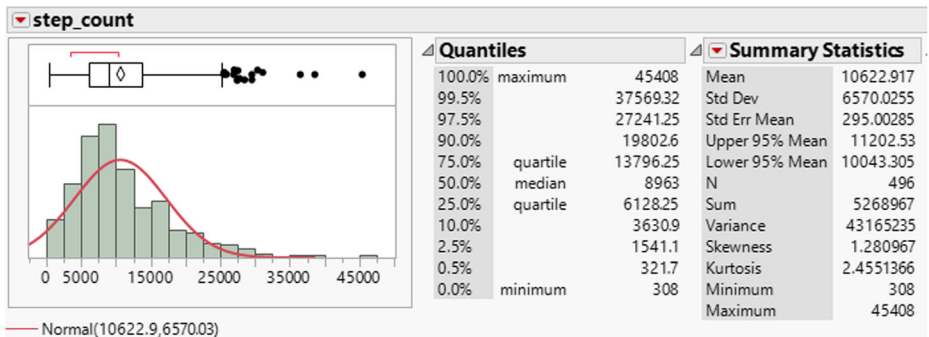Fig. 35 Community daily calories spent: males versus females

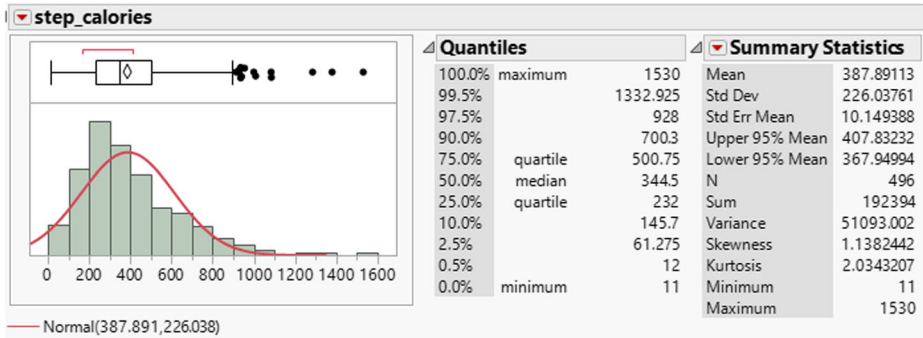Fig. 36 Daily data analytics for step count

step_calories

Quantiles			Summary Statistics	
100.0%	maximum	1530	Mean	387.89113
99.5%		1332.925	Std Dev	226.03761
97.5%		928	Std Err Mean	10.149388
90.0%		700.3	Upper 95% Mean	407.83232
75.0%	quartile	500.75	Lower 95% Mean	367.94994
50.0%	median	344.5	N	496
25.0%	quartile	232	Sum	192394
10.0%		145.7	Variance	51093.002
2.5%		61.275	Skewness	1.1382442
0.5%		12	Kurtosis	2.0343207
0.0%	minimum	11	Minimum	11
			Maximum	1530

— Normal(387.891,226.038)

Fig. 37 Daily data analytics for calories burnt during walking

steps_distance

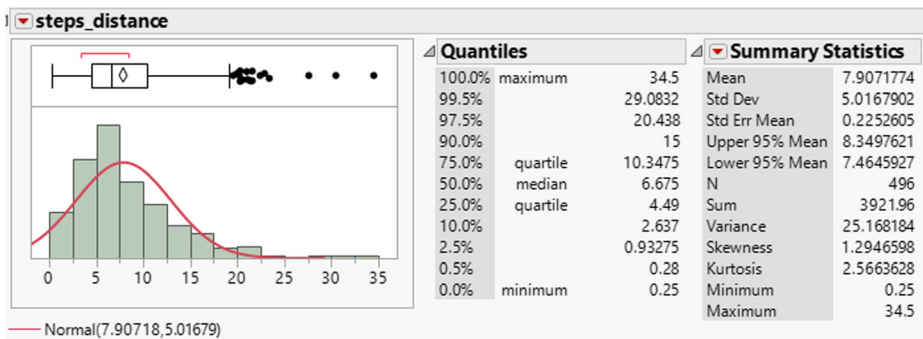| Quantiles			Summary Statistics	
100.0%	maximum	34.5	Mean	7.9071774
99.5%		29.0832	Std Dev	5.0167902
97.5%		20.438	Std Err Mean	0.2252605
90.0%		15	Upper 95% Mean	8.3497621
75.0%	quartile	10.3475	Lower 95% Mean	7.4645927
50.0%	median	6.675	N	496
25.0%	quartile	4.49	Sum	3921.96
10.0%		2.637	Variance	25.168184
2.5%		0.93275	Skewness	1.2946598
0.5%		0.28	Kurtosis	2.5663628
0.0%	minimum	0.25	Minimum	0.25
			Maximum	34.5

— Normal(7.90718,5.01679)

Fig. 38 Daily data analytics for distance covered whilst walking

Figure 52 which summarises the monitored activities, reveals a personal pattern that matches on some days only that of the community and may also suggest a sedentary lifestyle. Table 9 summarises the personal results and Figs. 53, 54 and 55 provide a comparison to the relevant community dataset and trends.

The data analytics models on Figs. 36, 37, 38, 39, 40, 41, 42, 43, 44, 45, 46 and Table 7 are used by GA and PO during the second part of *Step 5* to generate an initial population of
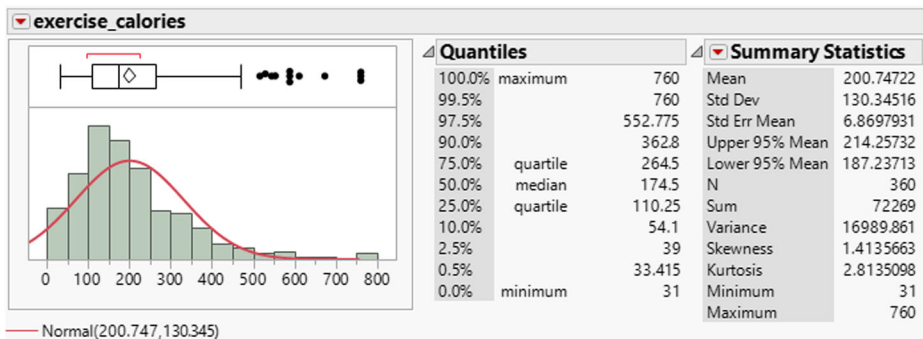
exercise_calories

Quantiles			Summary Statistics	
100.0%	maximum	760	Mean	200.74722
99.5%		760	Std Dev	130.34516
97.5%		552.775	Std Err Mean	6.8697931
90.0%		362.8	Upper 95% Mean	214.25732
75.0%	quartile	264.5	Lower 95% Mean	187.23713
50.0%	median	174.5	N	360
25.0%	quartile	110.25	Sum	72269
10.0%		54.1	Variance	16989.861
2.5%		39	Skewness	1.4135663
0.5%		33.415	Kurtosis	2.8135098
0.0%	minimum	31	Minimum	31
			Maximum	760

— Normal(200.747,130.345)

Fig. 39 Daily data analytics for calories burnt during exercising

exercise_distance

Quantiles			Summary Statistics	
100.0%	maximum	17	Mean	4.174411
99.5%		17	Std Dev	2.7665111
97.5%		12.2595	Std Err Mean	0.1448058
90.0%		7.562	Upper 95% Mean	4.459172
75.0%	quartile	5.3	Lower 95% Mean	3.88965
50.0%	median	3.67	N	365
25.0%	quartile	2.34	Sum	1523.66
10.0%		1.126	Variance	7.6535835
2.5%		0.8515	Skewness	1.655054
0.5%		0	Kurtosis	4.0874518
0.0%	minimum	0	Minimum	0
			Maximum	17

—— Normal(4.17441,2.76651)

Fig. 40　Daily data analytics for distance covered whilst exercising

exercise_duration

Quantiles			Summary Statistics	
100.0%	maximum	229	Mean	51.452055
99.5%		229	Std Dev	34.025944
97.5%		139.7	Std Err Mean	1.7809993
90.0%		93.4	Upper 95% Mean	54.954395
75.0%	quartile	63.5	Lower 95% Mean	47.949715
50.0%	median	46	N	365
25.0%	quartile	31	Sum	18780
10.0%		14.6	Variance	1157.7649
2.5%		11	Skewness	1.9295405
0.5%		0	Kurtosis	6.2367687
0.0%	minimum	0	Minimum	0
			Maximum	229

—— Normal(51.4521,34.0259)

Fig. 41　Daily data analytics for exercise duration

chromosomes and to source limit and optimisation constraints. The recommendations to the wearer will be sourced from the non-dominated chromosome that evolves, like the one which appears on Fig. 4. During **Step 6** the laptop transfers the daily models produced by JMP PRO and the recommendation generated by the GA and PO to the smartphone via the tracker's cloud servers. During **Step 7**, the data models and recommendation are visualised using

sleep_calories

Quantiles			Summary Statistics	
100.0%	maximum	735	Mean	492.41935
99.5%		726.03	Std Dev	97.675744
97.5%		703.725	Std Err Mean	4.3857704
90.0%		630	Upper 95% Mean	501.03638
75.0%	quartile	558.75	Lower 95% Mean	483.80233
50.0%	median	479.5	N	496
25.0%	quartile	420	Sum	244240
10.0%		379.7	Variance	9540.5511
2.5%		315.85	Skewness	0.2620433
0.5%		252.305	Kurtosis	-0.142642
0.0%	minimum	136	Minimum	136
			Maximum	735

—— Normal(492.419,97.6757)

Fig. 42　Daily data analytics for calories burnt during sleeping

sleep_duration

⊿ Quantiles		
100.0%	maximum	633
99.5%		624.18
97.5%		548.575
90.0%		530
75.0%	quartile	504
50.0%	median	473.5
25.0%	quartile	430.25
10.0%		383
2.5%		320.425
0.5%		195.735
0.0%	minimum	116

⊿ ▼ Summary Statistics	
Mean	462.21371
Std Dev	63.347643
Std Err Mean	2.8443932
Upper 95% Mean	467.80228
Lower 95% Mean	456.62514
N	496
Sum	229258
Variance	4012.9239
Skewness	-1.203266
Kurtosis	3.2089664
Minimum	116
Maximum	633

—— Normal(462.214,63.3476)

Fig. 43 Daily data analytics for sleeping duration

FitNalyser to support the wearer with monitoring their daily goals and activities and their weekly and monthly performance. The analysis of the personal dataset collated on the wearable device has picked up that the daily average of expended calories is approximately

Correlations

	step_count	step_calories	steps_distance
step_count	1.0000	0.9180	0.9878
step_calories	0.9180	1.0000	0.9296
steps_distance	0.9878	0.9296	1.0000

▼ Scatterplot Matrix
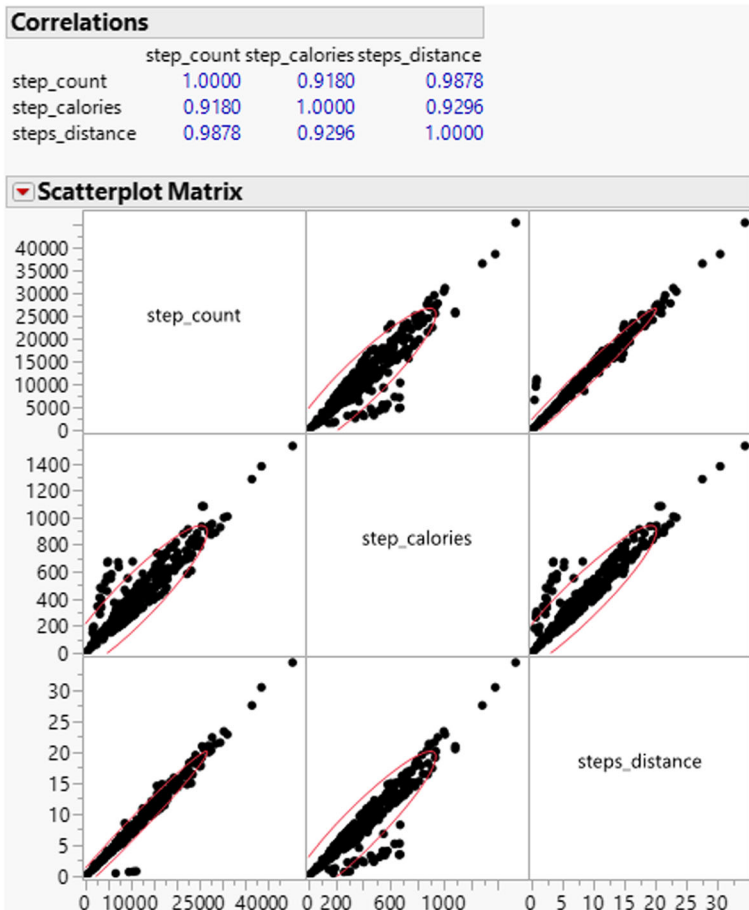
Fig. 44 Correlation between walking variables

🖄 Springer

25% less than the daily average a person with that BMI is expected to burn which in the long-term will result in weight gain and the chromosome and subsequent recommendation generated addresses that. There is clearly room for improvement in relation to calorie burning and the generated recommendation visualised on Fig. 14 reflects that. The wearer may wish to consider as much evidence behind this recommendation as possible and may also wish to consider their performance in relation to that of their peers. Figures 8 through to 13 provide all the daily and weekly evidence the wearer may seek. During *Step 8*, the wearer, having considered the evidence and recommendation, may revisit their current daily goals and activities, and set up new activity goals, e.g. reduce the number of hours spent sleeping, increase the number of hours spent walking, increase the step count, to move from sedentary to lightly active or active. During *Step 9*, the smart phone synchronises with the wearable to auto-update any revised goals. Not all wearables facilitate that but both wearables used in our experiment allow that.
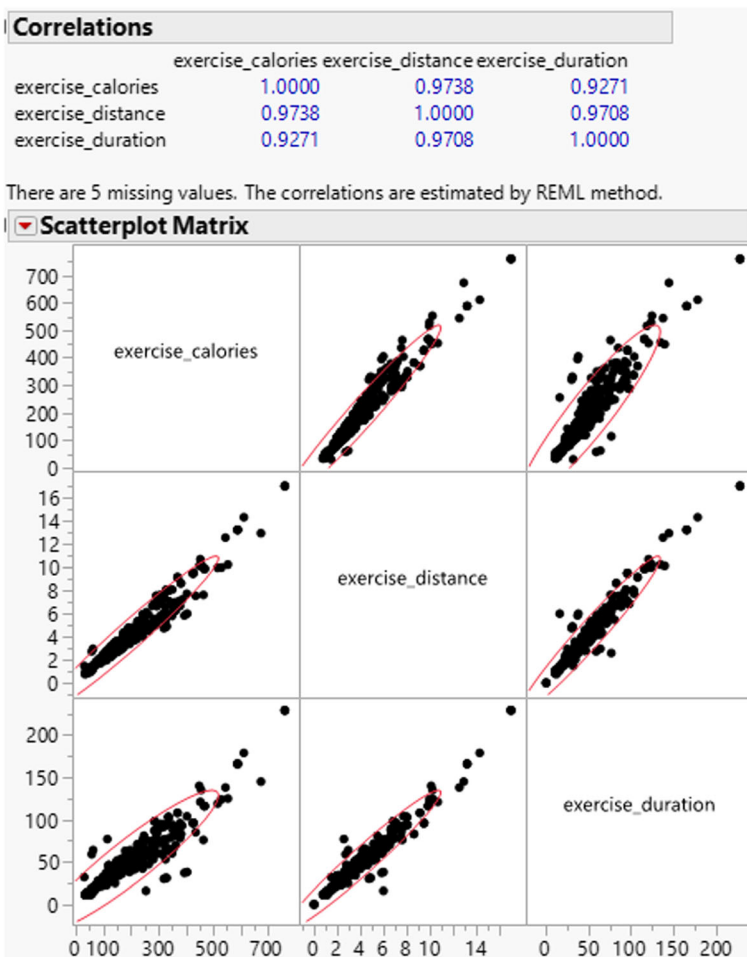
Fig. 45 Correlation between exercising variables

4.2 Bru-Fit

Steps 1, 2 and 3 are like FitNalyser's. Fitbit tracks sleep through movement using one of two modes, normal and sensitive. It records, as when awake, significant movements only in normal mode and nearly all movements in sensitive mode:

$$t_{asleep} = t_{Total\ tracked} - t_{awake}$$

$$Sleep\ Efficiency = 100 \left(\frac{t_{asleep}}{t_{asleep} + t_{restless} + t_{awoken\ during\ sleep}} \right)$$

Fitbit tracks the Heart rate through blood volume variation using LED lights onto the skin. It records the intensity of exercising as a percentage of:
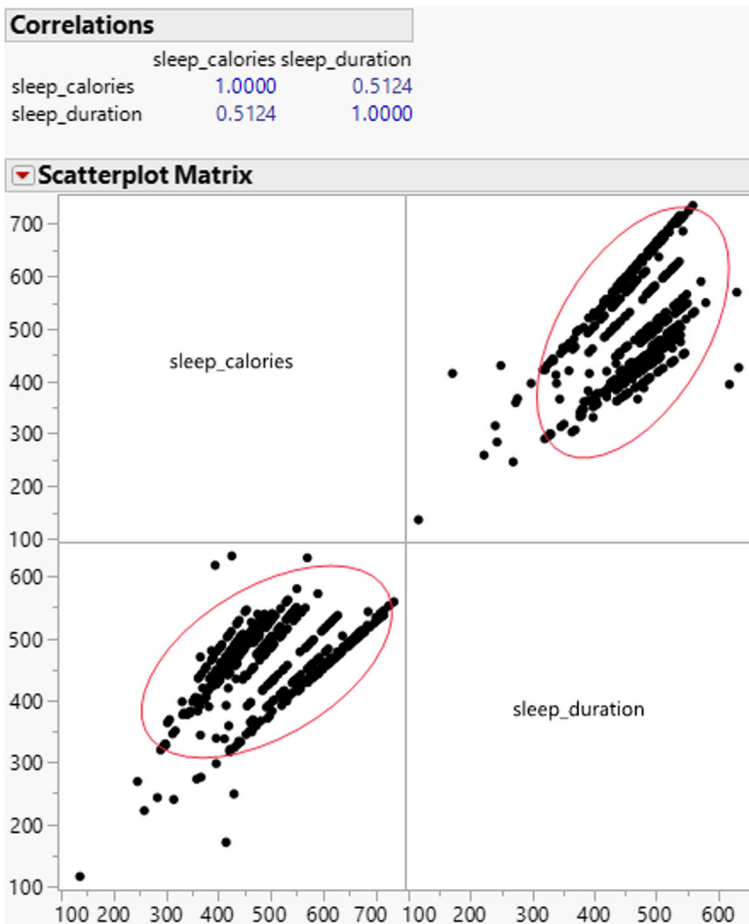
Fig. 46 Correlation between sleeping variables

Table 7 Full table of correlations

Correlations

	step_count	step_calories	steps_distance	exercise_calories	exercise_distance	exercise_duration	sleep_calories	sleep_duration
step_count	1.0000	0.9180	0.9878	0.3004	0.3302	0.3482	-0.1174	0.0700
step_calories	0.9180	1.0000	0.9296	0.2953	0.2963	0.3193	0.0015	0.0228
steps_distance	0.9878	0.9296	1.0000	0.2999	0.3240	0.3369	-0.0921	0.0589
exercise_calories	0.3004	0.2953	0.2999	1.0000	0.9780	0.9373	-0.0908	-0.1317
exercise_distance	0.3302	0.2963	0.3240	0.9780	1.0000	0.9746	-0.1692	-0.0989
exercise_duration	0.3482	0.3193	0.3369	0.9373	0.9746	1.0000	-0.1652	-0.0834
sleep_calories	-0.1174	0.0015	-0.0921	-0.0908	-0.1692	-0.1652	1.0000	0.5124
sleep_duration	0.0700	0.0228	0.0589	-0.1317	-0.0989	-0.0834	0.5124	1.0000

Table 8 Daily activity trends

	Step count	Step calories	Steps distance (km)	Exercise calories	Exercise distance (km)	Exercise duration (min)	Sleep calories	Sleep Duration (min)
Monday	8580	315	6.44	193	3.80	47	382	359
Tuesday	8261	317	6.29	210	4.19	52	377	359
Wednesday	8572	317	6.38	164	3.16	40	391	370
Thursday	8555	308	6.30	184	3.48	45	403	377
Friday	13731	502	10.11	118	2.09	27	632	595
Saturday	13169	475	9.76	186	3.02	43	618	576
Sunday	12968	459	9.64	216	4.60	55	624	579

Fig. 47 Daily calories burned
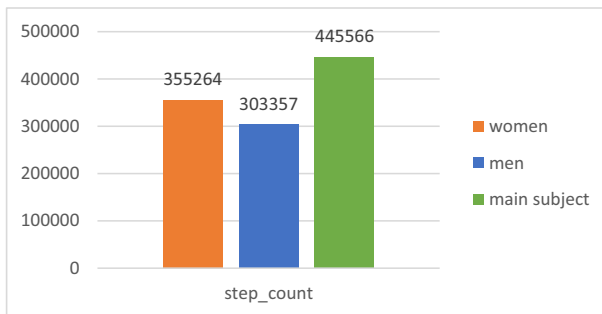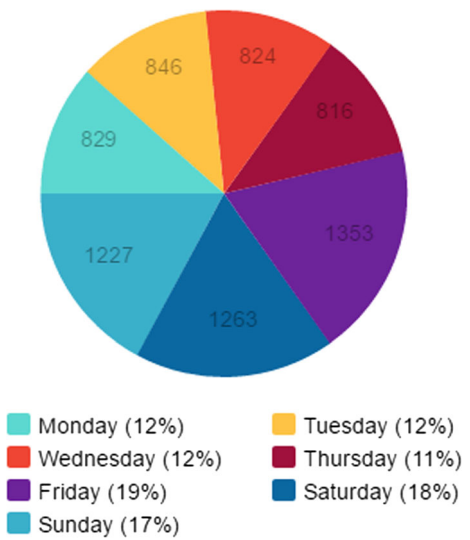
Fig. 48 Monthly step count
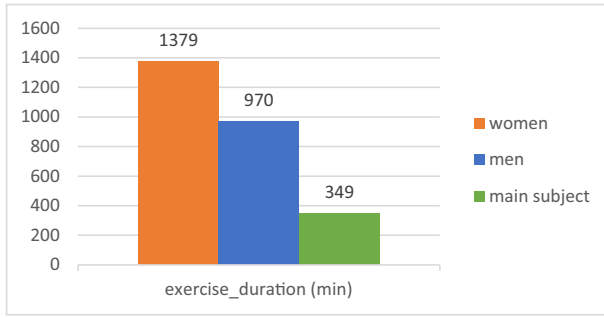
Fig. 49 Monthly exercise period
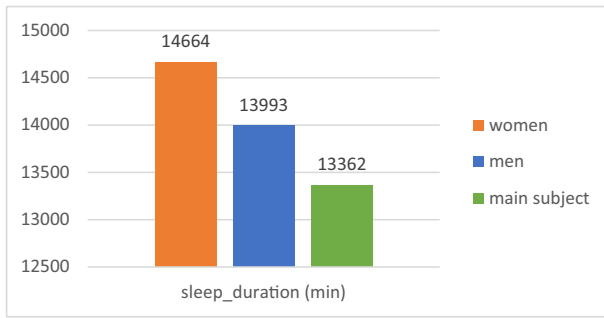
Fig. 50 Monthly sleep period
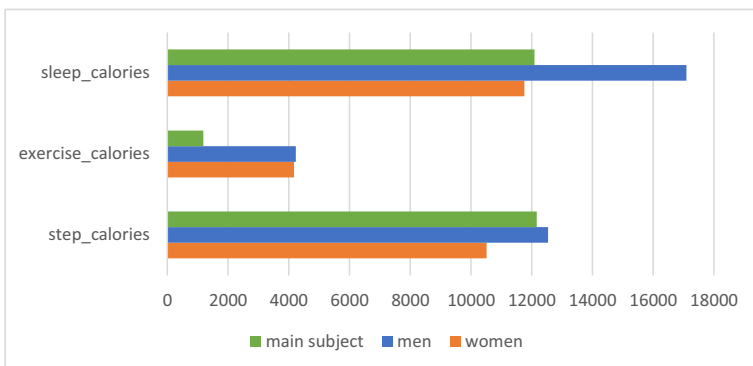
Fig. 51 Monthly comparison of calories burnt

Days	Step count		Exercise duration		Sleep duration	
	Main Subject	Dataset	Main Subject	Dataset	Main Subject	Dataset
Monday	14547	8580	37	47	378	359
Tuesday	15776	8261	31	52	442	359
Wednesday	10731	8572	36	40	466	370
Thursday	14834	8555	26	45	401	377
Friday	15771	13731	27	27	465	595
Saturday	13305	13169	43	43	433	576
Sunday	15328	12968	48	55	425	579

Fig. 52 Personal against community trends

Table 9 Personal results

Gender	Female
Age	28 years old
Weight	54.4 kg
Height	154 cm
BMI	22.94 (Healthy weight)
Daily calories burnt	1173.5
Activity level	Sedentary
Daily average step count	14373
Daily average exercise duration	35 min (2 days per week)
Daily average sleep duration	431 min
Personal trends in relation to community group	step count = normal; exercise duration = poor; sleep duration = normal

$$Maximum \quad rate = 220 - age$$

This rate decreases with age, thus seeking to acheve the same level of intensity across different age groups requires different amounts of effort. Table 10 shows Fitbit's five intensity zones as a percentage of Heart rate.

Fitbit tracks activity and calories burned through exercise intensity using Steps, Floors and Heart Rate along with Metabolic Equivalent (MET), BMR, weight and height. BMR values
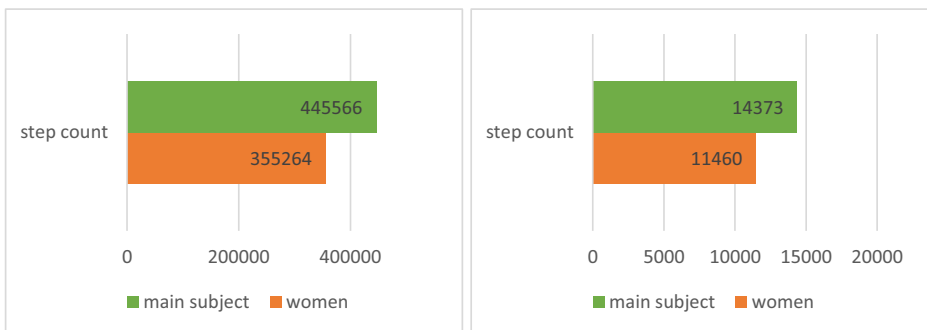
Fig. 53 Personal against community step count
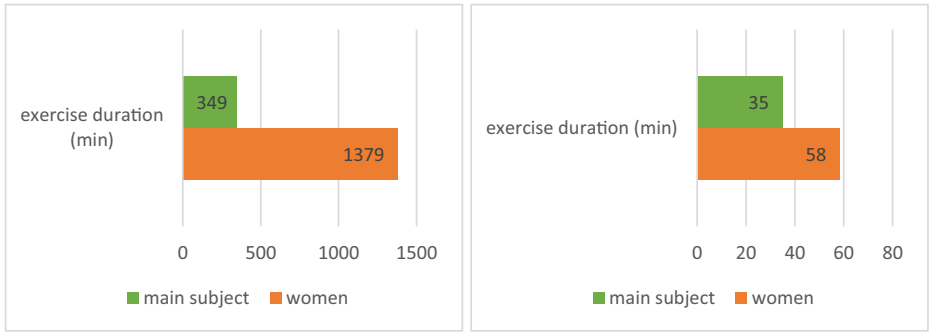
Fig. 54 Personal against community exercise duration
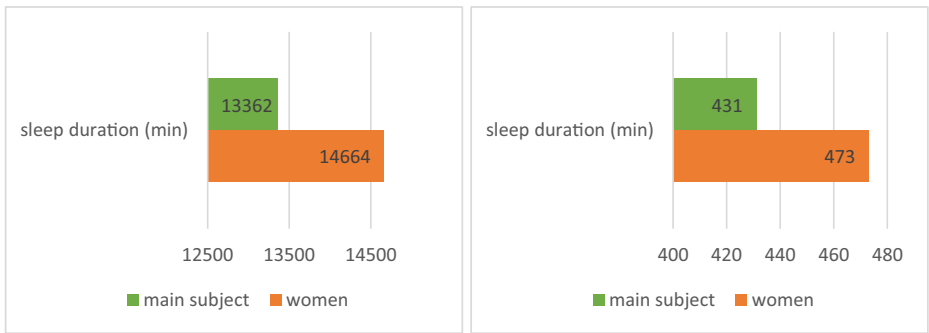
Fig. 55 Personal against community sleep duration

Table 10 Fitbit heart rate zones

Effort		Effect
Peak zone	85% of maximum rate	High-intensity exercise zone
Cardio	70 to 84% of maximum rate	Medium-to-high intensity exercise zone
Fat burn zone	50 to 69% of maximum rate	Low-to-medium intensity exercise zone
Out of zone	Below 50% of maximum rate	Not enough to be considered exercise
Resting	60-80 beats per minute	Awake, calm, comfortable, not recently exerted yourself

Table 11 Fitbit parameters tracked

Parameter	Variable
Sleep	Time in bed
	Actual Sleep Time
Activities	Minutes Sedentary
	Minutes Lightly Active
	Minutes Fairly Active
	Minutes Very Active
Steps	Number of Steps
Floors	Number of Floors
Calories	Number of Calories burned

Classification of partipants according to Age
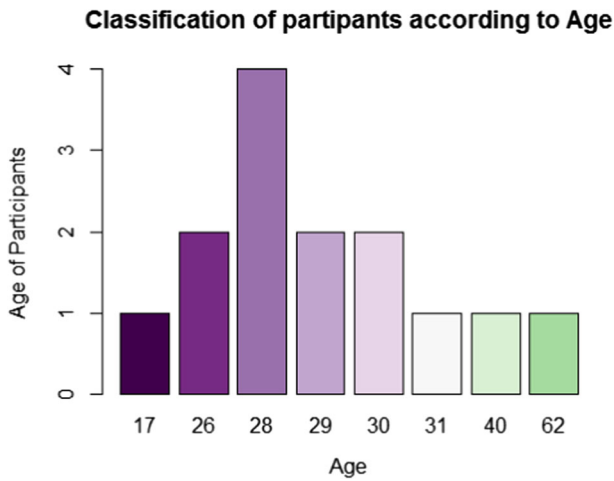
Fig. 56 Participants by age

usually account for at least half of the calories burnt in a day and this is estimated based on gender, age, height, and weight. Table 11 shows the Fitbit parameters tracked.

A significant difference between Bru-Fit and FitNalyser takes place during **Step 4**, during which a Fitbit open script executes the transfer to a laptop via Fitbit's cloud servers of the raw dataset which has been packaged into a cvs file. **Step 5** is like FitNalyser but the wearer and the peer group comprise different wearers. The community group comprise of 14 different wearers, 6 women and 8 men and their dataset includes both qualitative and quantitative data: Age, gender, height, weight, BMI, calorie stats (maximum, minimum, average, daily, weekly, monthly), activity stats (level, frequency), step stats, floor stats, distance, sleep stats (daily patterns, efficiency). Figures 56 and 57 classify participants by age and gender respectively. Figure 58 maps the daily average of number of calories spent across the community. The figure reveals a mixture of distribution across the

Classification of partipants according to Gender
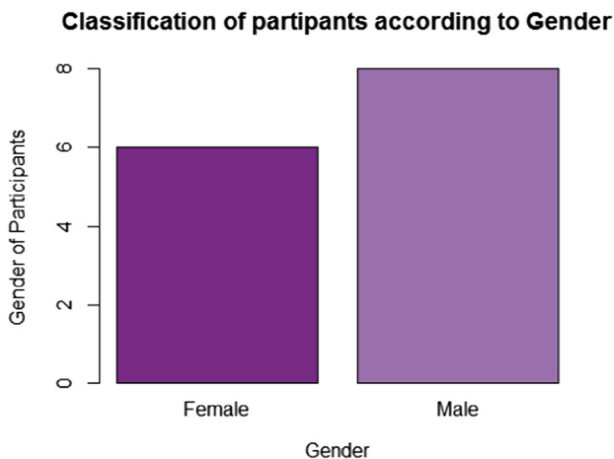
Fig. 57 Participants by gender
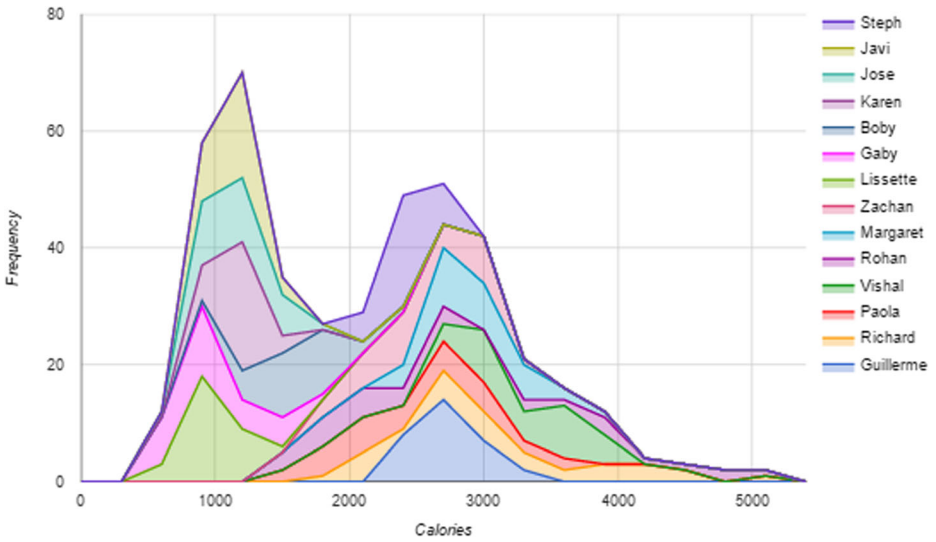
Fig. 58 Daily average of number of calories spent across the community
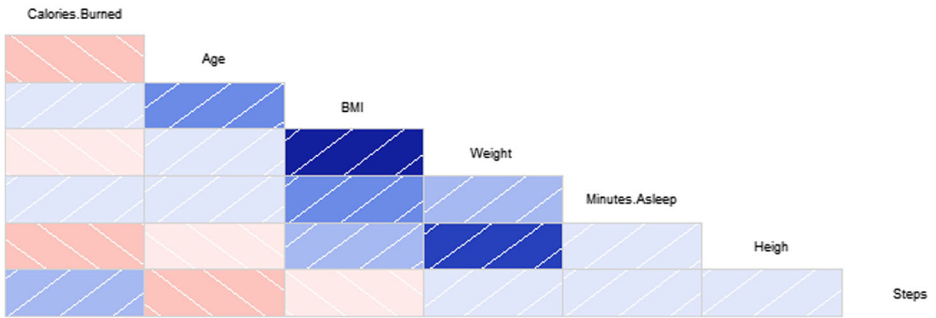
Fig. 59 Parameter correlation
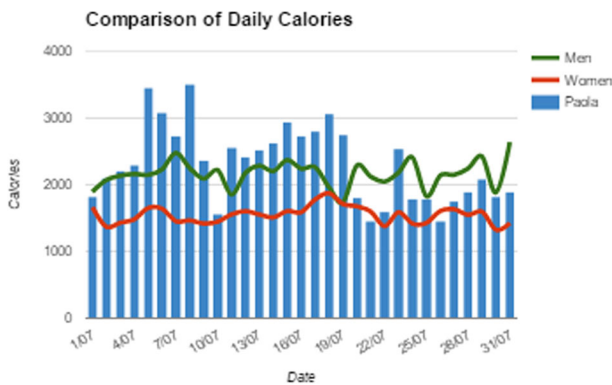
Fig. 60 Daily calories spent: Personal vs community
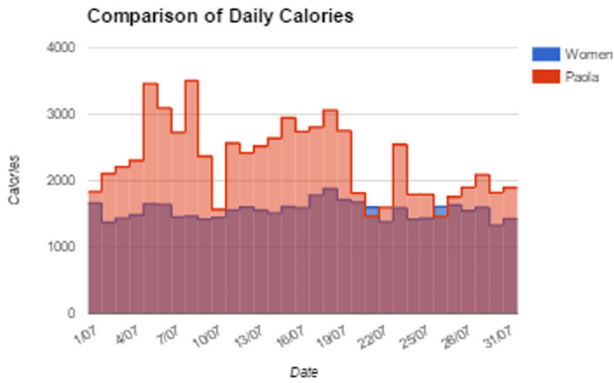
Fig. 61 Daily calories spent: Personal vs community females
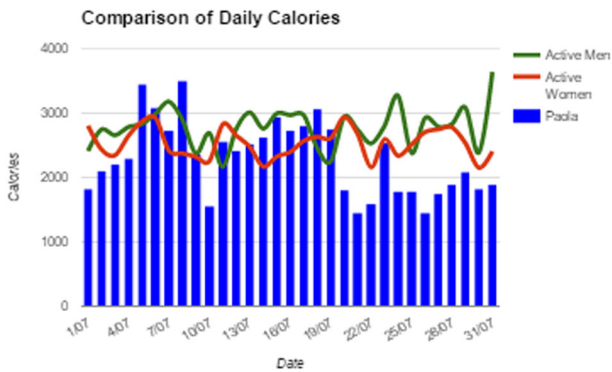
Fig. 62 Daily calories spent: Personal vs Lightly Active community members
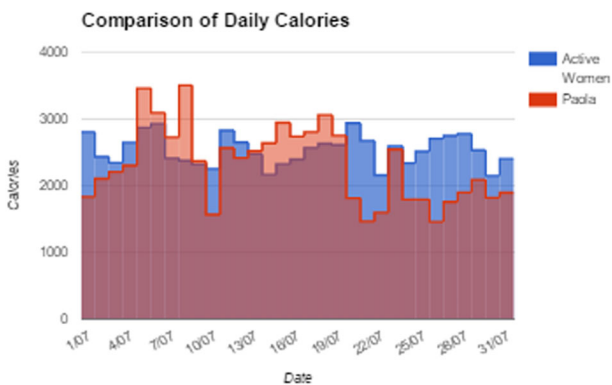
Fig. 63 Daily calories spent: Personal vs Lightly Active community females
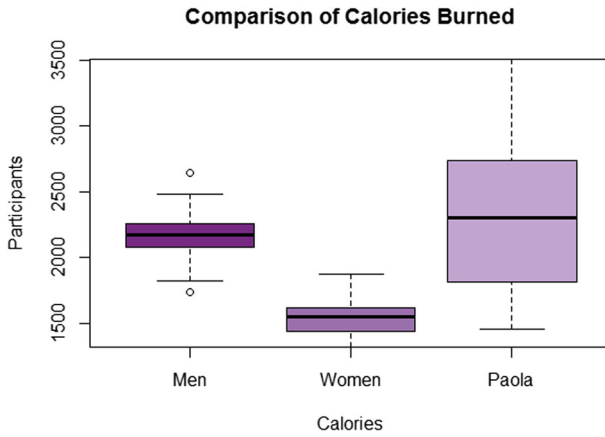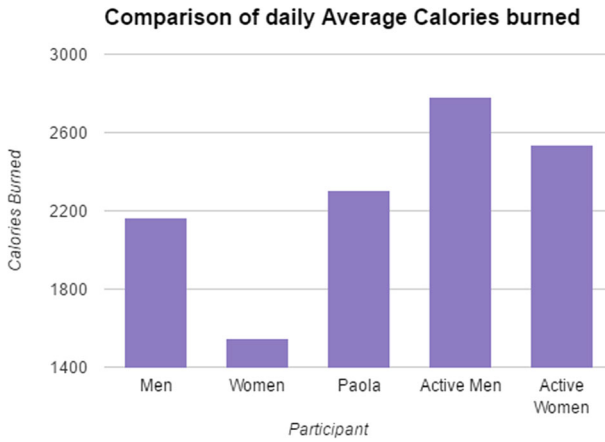
Fig. 64 Daily calories spent: Personal vs community

Fig. 65 Daily average calories spent: Personal vs Active community
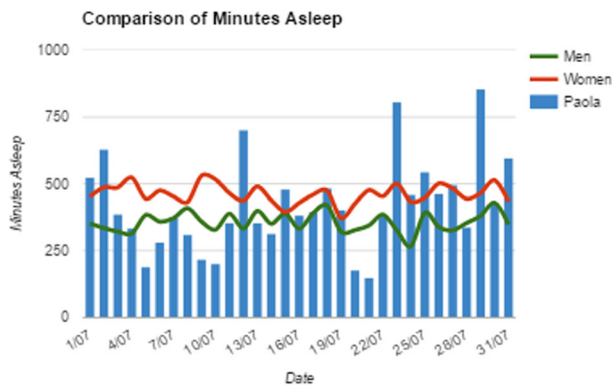
Fig. 66 Daily sleep: Personal vs community
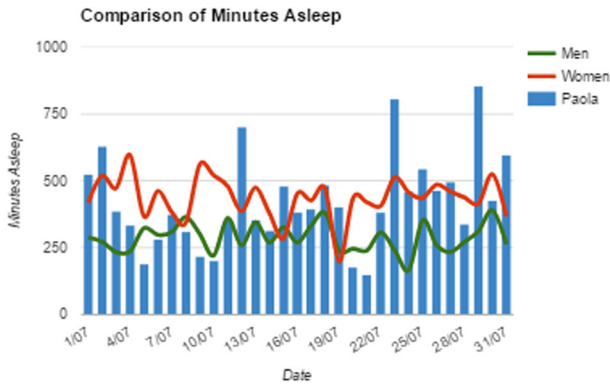
Fig. 67 Daily sleep: Personal vs community females
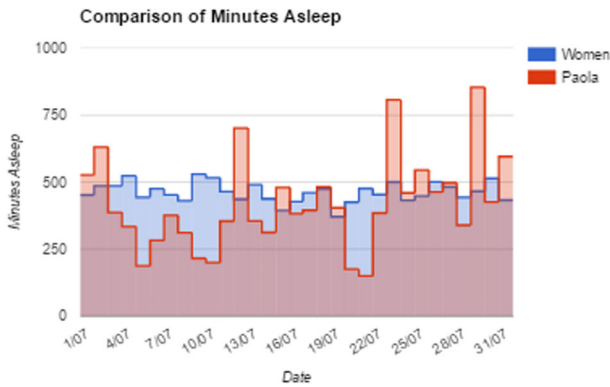
Fig. 68 Daily sleep: Personal vs Lightly Active community members
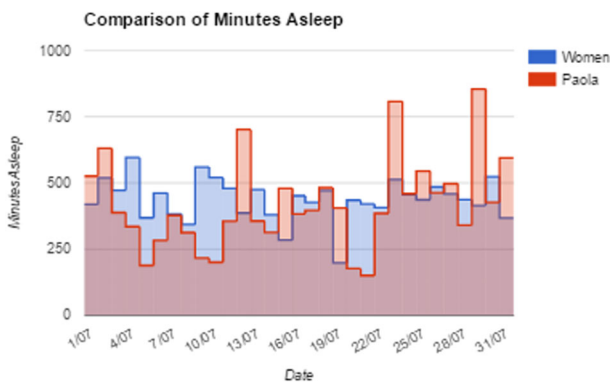
Fig. 69 Daily sleep: Personal vs Lightly Active community females
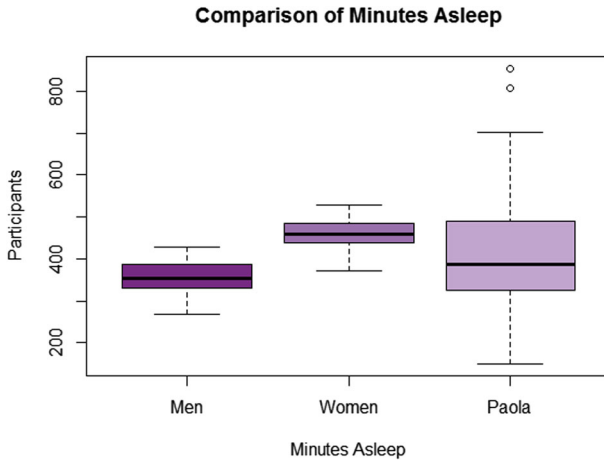
Fig. 70   Daily sleep: Personal vs community
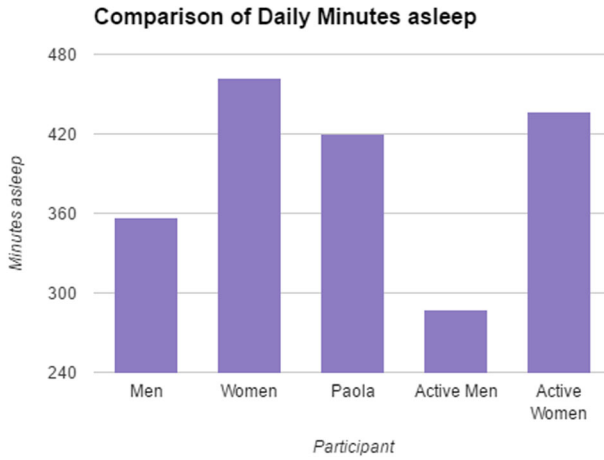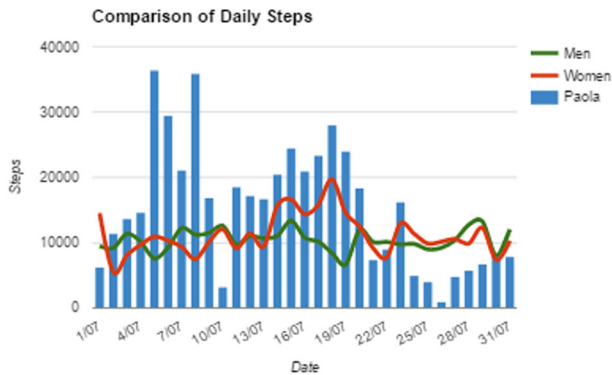

Fig. 71   Daily average sleep: Personal vs Active community

Fig. 72   Daily steps: Personal vs community
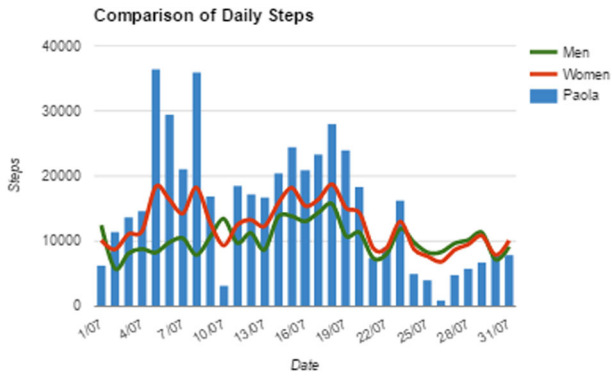
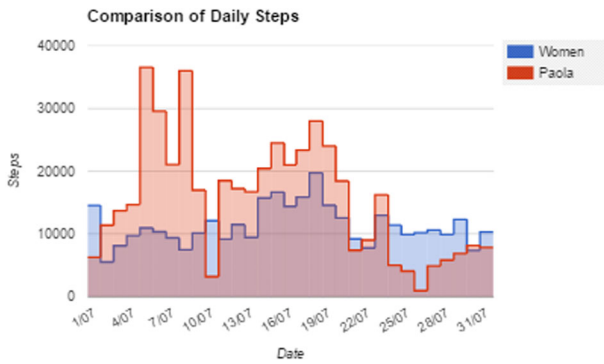**Fig. 73** Daily steps: Personal vs Lightly Active community members

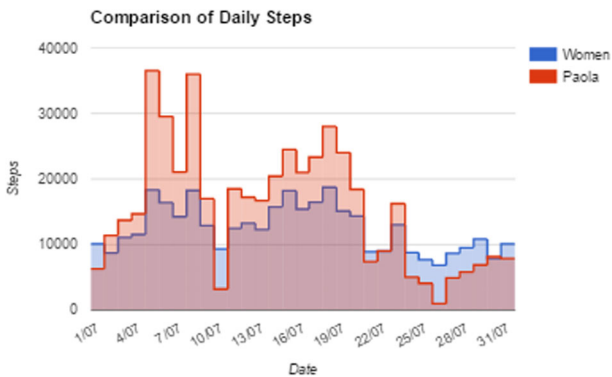**Fig. 74** Daily steps: Personal vs community females
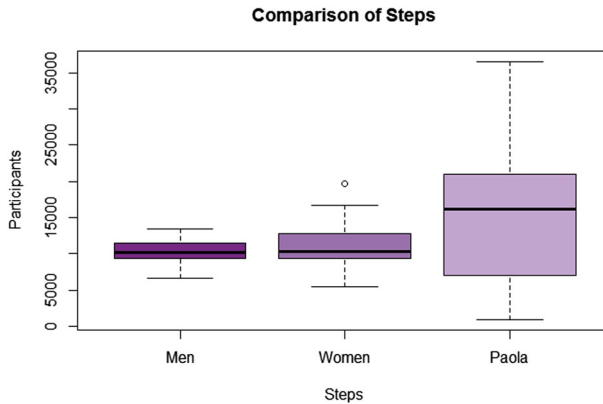

**Fig. 75** Daily steps: Personal vs Lightly Active community females

Fig. 76 Daily steps: Personal vs community

community, positively skewed because of low number of calories spent and normal. This splits the community into sedentary or lightly active.

Figure 59 shows parameter correlation. Red highlights indicate no positive correlation has been established whereas blue highlights indicate positive correlation. The correlation becomes stronger as the shade becomes darker. Unlike with FitNalyser, the correlation map does not indicate a correlation between daily activity and sleep.

Figures 60, 61, 62, 63, 64 and 65 compare the number of calories spent between the wearer and the community datasets. The results are attributed to females normally having a higher MBR than males because of having, in general, a higher percentage of fat to muscle in comparison to males who have, in general, a higher percentage of muscle to fat. Figures 66, 67, 68, 69, 70 and 71 show the outcome of tracking sleep activity. The figures reveal a higher sleep activity in males than in females. Figures 72, 73, 74, 75, 76 and 77 show the outcome of tracking daily steps through walking. These figures reveal a higher walking activity, and thus steps, by males than females in sharp contrast to past studies which report the reverse.

A second significant difference between Bru-Fit and FitNalyser takes place during *Step 6*, at which a Fitbit open script executes the transfer back to the smartphone via Fitbit's servers of
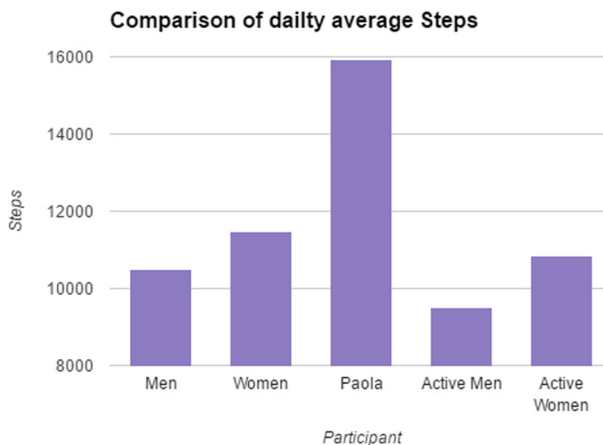
Fig. 77 Daily average steps: Personal vs community

the models produced by JMP PRO and the recommendations generated by the GA and PO. At *Step 7*, the analysis of the personal dataset collated on the wearable device has picked up that that the wearer has exceeded their daily goals with midweek being the most active days and Sundays the least active with walking being the most popular activity. Daily tracking of sleep efficiency has picked up that this rises during weekdays but declines at weekends despite a higher sleep activity during weekends. There were also significant variations in sleep efficiency across community members belonging to the same age group. This may be attributed to circadian rhythm sleep disorder CRSD which is common among younger generations. The results also reveal that males are more likely to be overweight and fall into the sedentary range than females are. Unlike FitNalyser the figures do not correlate sleep and daily activity. There is clearly room for improvement in relation to physical activity and sleeping at weekends and the generated recommendation visualised on Fig. 29 reflects that. The wearer may also wish to consider as much evidence behind this recommendation as possible and may also wish to consider their performance in relation to that of their peers. Figures 17 through to 28 provide all the daily and weekly evidence the wearer may seek. During *Step 8*, the wearer, having considered the evidence and recommendation, may revisit their current daily goals and activities, and set up new activity goals, e.g. reduce the number of hours spent sleeping and increase the number of hours spent walking. During *Step 9*, the smart phone synchronises with the wearable to auto-update any revised goals. Figure 17 shows how goals set on this wearable are visualised with Bru-Fit.

5 Concluding discussion

The paper demonstrates how wearable technology may be used beyond the hype to improve personal lifestyles by suggesting areas where generating a change in daily or routine habits may lead to a healthier lifestyle. Currently, such cycles appear to be driven by irrelevant or incomplete information which may not be easy to interpret but under peer pressure and the fear of exclusion, wearers adopt *ad hoc* change regardless. Our research and development work demonstrates that a planned approach to data collection, analysis and visualisation coupled with a machine learning recommender approach may transpose wearer decisions to be informed and that the use of peer group data is for generating correlated recommendations not for applying social pressure. A mobile app might not be able to support the entire cycle and consequently backbone computing support is required. The analysis has also thrown some accepted truths into dispute, i.e. the correlation between exercising and sleeping is very low suggesting the two are more independent than once thought. This might be the result of exogenous factors such as workstyle or underlining health conditions such as cardiovascular diseases. Areas for further research and development naturally include, in addition to the rising need for standardisation, the addition of more sensors to track further personal fitness and alarms to warn of the possibility of ambulatory incidents, an approach recently put on trial by the National Health Service (NHS) in the UK. This would raise the significance of the personal recommendations, especially in the health sector, but this would require a more extensive clinical trial as it would have serious repercussions to health and fitness. Finally, suggestions of automatic readjustment of personal goals following a recommendation, i.e. without wearer intervention, has divided the community after clinicians recommend that this should only be encouraged under clinical supervision.

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