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# Exercise monitoring of young adults using a Facebook application

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## Abstract

Facebook, with a record 1.7+ billion monthly active users, is increasingly the platform of choice for a multitude of e-health applications. This work presents our experience in exercise monitoring using a custom-built Facebook application for activity self-reporting. A group of young adults ($n = 49$, age $= 24 \pm 7$ years, body mass index (BMI) $= 22.5 \pm 3$) took part in a 5-week pilot study, part of the NutriHeAl intervention project. Participants reported their daily exercise activities for an average of $33 \pm 5$ days and were also equipped with digital pedometers (Fibit Zips) for the full duration, allowing the evaluation of their activity reporting accuracy by comparing steps/min to a 'truth ceiling' value for two pre-defined exercise categories (2+ and 3+ metabolic equivalent of task (MET) intensity). We found that users not only reported their exercise consistently for an extended period of time but also achieved an average accuracy score of $71 \pm 21\%$ ($82 \pm 18\%$ for 2+ MET exercises), making this novel exercise monitoring methodology a formidable tool for a modern physician's digital arsenal. In addition, the developed tools and processes can also be re-used in other e-health applications.

## Keywords

E-health, exercise monitoring, Facebook app, Fitbit Zip, physical activity, social media

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## Introduction

The process of collecting and managing self-reported exercise data is essential in many health disciplines. For example, physical activity diaries are, in conjunction with food diaries, one of the most important tools in gathering patient data in nutrition and dietetics.[1,2] Such subjective methods ('direct observations, diaries, activity logs, recall and questionnaires') are popular methods for quantifying a selected variable (e.g. physical activity) due to their relatively low cost and the added value of contextual information provided by the user.[3] This is especially true in large-scale studies, where cost and ease of deployment can become a very important factor in the overall success and results of the study.

Using Web and Internet technologies, many of these methods can be digitized and provided online in various Web spaces, such as online social networking (OSN) websites, which have known increasing popularity over the last years. Facebook, specifically, has recently reached a phenomenal 1.7 billion+ monthly active users [http://www.statista.com/statistics/264810/number-of-monthly-active-facebook-users-worldwide]. As expected, the popular website's penetration is also high in young adult groups across the world (e.g. 87% in the United States, aged 18–29).[4] With such a high volume of users, OSN websites can be used as platforms for a variety of e-health applications[5] such as activity monitoring.

This pool of pre-existing users (people that already use Facebook for their own purposes) has a distinct benefit; there's a high chance that some of the users which will take part in a monitoring or intervention

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scenario are already on the platform, simplifying account management, link/questionnaire distribution and similar technological start-up costs.

However, data on OSNs is mostly unstructured and usually provided for different purposes. Social networking applications ('SNApps') are applications, usually Web-based or mobile-phone-based, that are linked to OSNs using pre-built Application Programming Interfaces (APIs). These applications can guide a user into providing structured data while, at the same time, making metadata (such as social data or app usage data) available to the application's developer. Since a SNApp is not a separate program, it removes the additional step many 'logging' participants in studies have to take in order to record data.

This work presents the design and evaluation of a SNApp on Facebook (a Facebook app) that was used in the NutriHeAl project [http://www.nutriheal.gr], a nutrition and physical activity intervention program targeted to Greek municipalities. We argue that a SNApp like this is an accurate, low-cost tool for online physical activity data collection. This application was tested in 49 young adults in order to monitor their physical activity over time. Furthermore, in order to assess the effectiveness of a SNApp as a self-reported activity monitor, a methodology to assess data collection accuracy using digital pedometer data has been developed and applied to the data collected.

The overall goal of this work is to (a) present the developed tools and processes which can easily be re-used in many e-health applications as well as (b) assess the accuracy and applicability of such an exercise monitoring methodology in order for it to be used by health professionals.

## Background

Facebook groups (dedicated, potentially closed spaces that facilitate content sharing between group members [https://www.facebook.com/help/284236078342160]) have been used in the past for intervention programs that promoted and monitored physical activity, by uploading relevant information and resources as group 'wall posts' and/or collecting data by encouraging users to answer self-reported questionnaires.[6–9] Although Facebook groups are an easy, accessible choice for OSN-based e-health research, Facebook also offers a very well documented, free and versatile platform for application development [https://developers.facebook.com/] which allows researchers to provide custom content and easily benefit from the existence of both social data and user-generated content in the same platform.

A Web developer can build an application that could be as simple as an HTML Web form accessed from Facebook and offer it to the public or a selected audience. In addition, the developer can specifically request to access the users' data that exists on the platform (social data, likes, interests etc.). Over 1 million users use health and fitness SNApps such as MyFitnessPal [https://www.facebook.com/games/myfitnesspal_fb/], which aids users in keeping a food and exercise journal, among other features. A recent study showed that exercise (mobile) app users are more likely to exercise during their leisure time (one of the most important times for exercise),[10] compared with those who do not use exercise apps.[11]

Although Facebook apps are an established staple of the popular OSN and the number of potential users is extremely large, to date only a handful of peer-reviewed studies have explicitly used one for exercise monitoring. Foster et al.[12] use a Facebook app where participants (10 co-workers in a UK hospital) self-report their daily step count. The same concept of daily steps self-reporting is also used in Maher et al.,[13] where 110 adults (mean age 35.6 years) participated in an intervention for insufficiently active adults via Facebook. The 'Mums Step It Up'[14] program in Australia, aimed at mothers with young children, also tracks daily steps via a Facebook app throughout a 28-day period and assesses physical activity by distributing the Active Australia physical activity questionnaire.[15] Ding et al.[16] developed a physical activity monitoring and sharing platform (PAMS) for manual wheelchair users where a Facebook app was used for monitoring and sharing users' progress, as reported by a monitoring unit installed on the wheelchair. It is worthwhile to note that in all the above studies, daily physical activity levels were increased.

To the best of our knowledge, this work presents the first related research effort that uses a Facebook app as an activity diary for self-reporting exercise in detail. In addition, although digital pedometers step counts have been used in the past as a self-reported variable, in this work they are automatically retrieved (with no room for self-reporting error) and are used for determining the accuracy of self-reported exercises.

## The NutriHeAl Facebook application

The app, built for the purposes of the NutriHeAl project and based, in part, on previous work in the same area[17–19] is entitled 'NutriHeAl Activity Diary'. It was accessible publicly through Facebook for the duration of the specific project work package and requires a valid Facebook account to use. The app is currently only available in Greek but there are plans to provide full translation packages for re-use, as the application has an abstract design approach that can be used in similar research projects. The screenshots presented hereafter use a beta version of the English translation package.

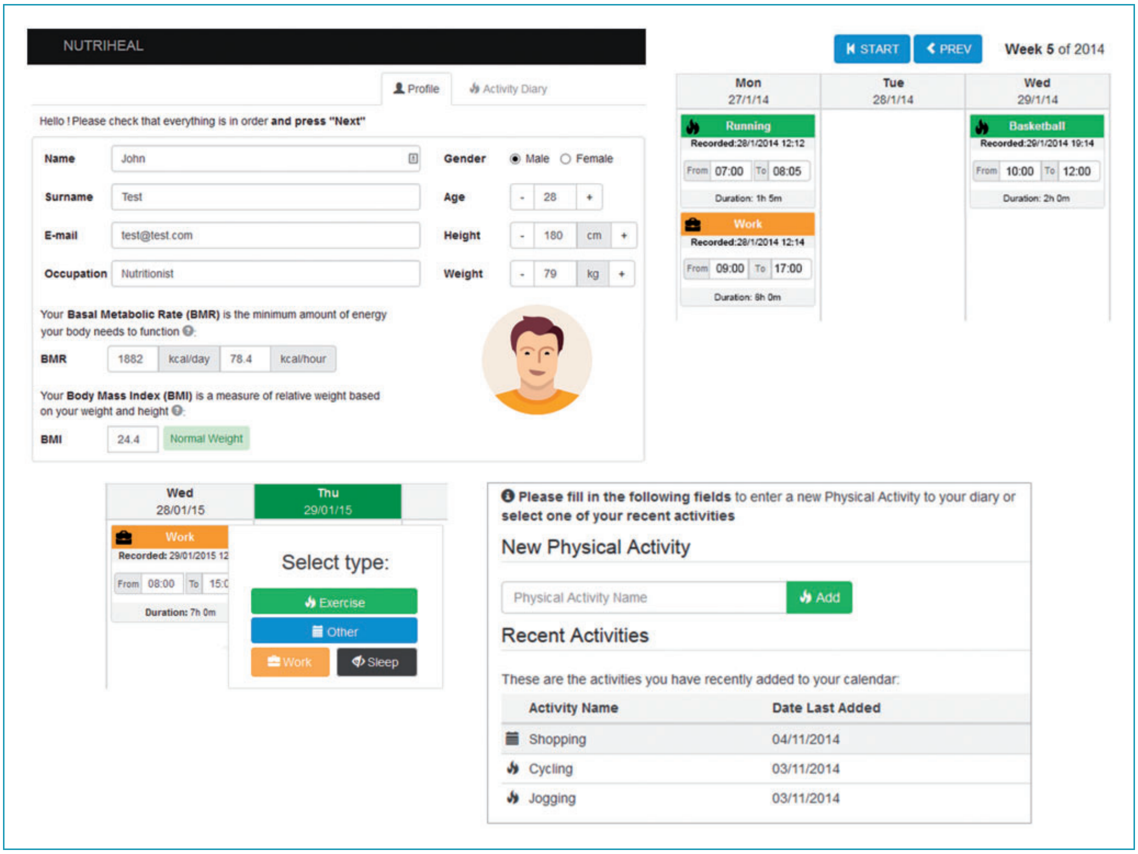


**Figure 1.** The NutriHeAl Facebook app

Technically, the app is a W3C standards-compliant website (built with HTML, PHP and frameworks like Bootstrap and jQuery [http://getbootstrap.com, jQuery: http://jquery.com]) that is hosted on a private server and 'served' through the Facebook canvas. This allows it to use its own design as well as store its own data, while at the same time benefiting from the Facebook environment integration. What this means, in practice, is that users who click on a link to use the app (e.g. from a Facebook news post, or a post in a Facebook group) 'stay' in the Facebook environment which allows them to use all the Facebook services (chat, notifications etc.) while at the same time accessing the application. In our opinion, this also helps to motivate users to use the app while on Facebook, as they do not feel like they have to leave Facebook and stop what they are doing to do so.

When using the application for the first time, users are presented with a Facebook-controlled mandatory dialog which allows them to either accept or deny the permissions required by the app. Apart from the standard public profile data, the NutriHeAl app only requests the user's *list of friends*, which – as discussed later – can be used for a multitude of purposes. The app's privacy policy (according to Facebook Policy [https://developers.facebook.com/policy]) explicitly states that social connection data may be used anonymously for further research and social network analysis.

After authorizing the app, users are presented with the app's homepage. The data collection methodology is based on a two-step approach, visualized through a tabbed interface. The first tab (Profile) collects the user's basic information and the second tab (Activity Diary) contains a weekly calendar where users can add their daily activity (an activity diary). The third tab (Results) requires no user input and shows result graphs that combine Fitbit and app data.

## *Profile tab*

In the Profile tab (Figure 1, top left), users enter their name, surname, email and occupation as well as their sex, age, height and weight (self-reported). The app uses these to automatically calculate the user's body mass index (BMI), basal metaboic rate (BMR) and BMR/hour (using the Schofield equation [20]), briefly explain what they are and provide feedback in the case of BMI (using the BMI classification as established in the WHO 2000 report[21]). By hovering over the '?' icon, the user can get more information in regards to these metrics.

Both the self-reported data (e.g. age, weight, height) and the data calculated by the app (BMI, BMR) are saved in a database when the user proceeds to the next tab. As mentioned before, this database is not related to Facebook in any way and is stored in a separate, secure environment.

## Activity Diary tab

The Activity Diary tab is an interface that resembles a weekly calendar (Figure 1, top right), where users are able to add a new activity by double-clicking on the empty 'white space' of each day. The users are then presented with a dialog (Figure 1, bottom left) which allows them to (a) *add a custom 'exercise'* (e.g. 'walking', 'running', typed in by the user) *or 'other'* (e.g. shopping, sweeping) activity or (b) select one of two *pre-defined activities* – sleep and work.

In order for users to record activities in a detailed manner, a common approach is to utilise a pre-populated activity table for exercise entry such as the well-known *Compendium of Physical Activities*.[22] In our pre-pilot tests with a focus group of five participants, it was quickly established that users have difficulty finding and selecting the correct exercise without the presence of an expert. Users would ordinarily miscalculate their walking or jogging speed, select the wrong type of stationary bicycle activity when in the gym etc. This is an expected outcome and not an issue with the Compendium itself or related indices, as they are typically designed for a different purpose (e.g. comparing metabolic equivalent of a task (MET) values between activities).

An alternative approach, which was utilised in the NutriHeAl app, is to allow users to specify most of the activities themselves as 'free text'. When the system keeps a record of past activities and allows users to quickly re-add them (Figure 1, bottom right, 'recent activities'), we found that our focus group displayed a very low (5–6 s) turnaround time in adding a new activity to their diary. This also makes it easier for users to enter their data often.

## Results tab

These personalised graphs, an example of which can be seen in Figure 2, show the user's reported activities as an overlay to recorded digital pedometer data and were accessible only by the specific participant and the overseeing nutritionist (using a username/password combination). Participants were informed when viewing the logs that their physical activity is not going to be visible by others within their network. These graphs can be used in multiple ways, such as an incentive for users to submit exercise data in order to later view their relation to the steps recorded by the Fitbit. This is a similar approach to what many of the digital pedometer mobile phone apps (including Fitbit) can do, but has the added advantage of using the same interface and environment as the pilot study app.

In the pilot study, results tabs were used to encourage participation and maintain users' interest, as the Fitbit data were not made available to participants.

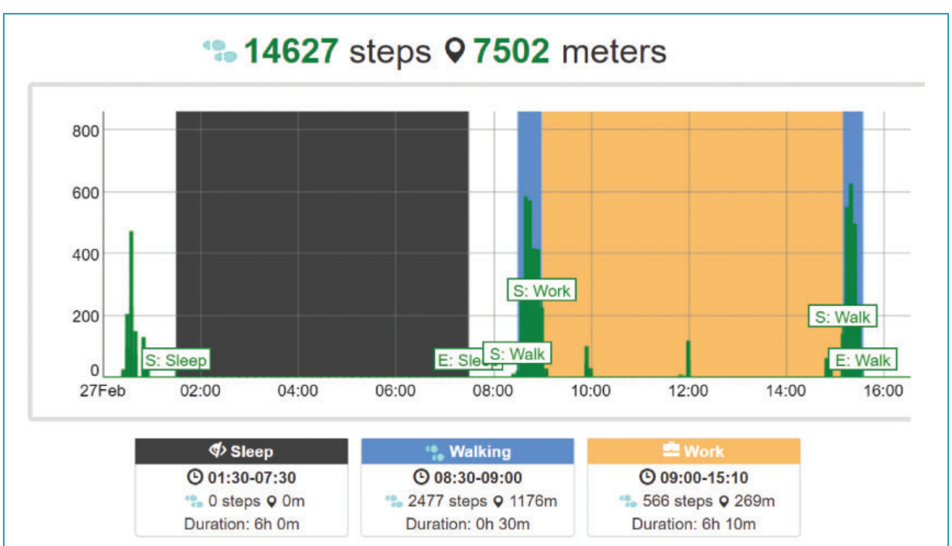


**Figure 2.** Example of a result graph

If other incentives are available within an intervention, or digital pedometers are not used at all, results tabs can be optional or used only for data aggregation (e.g. building an intervention moderator's overview screen).

## Methodology

### Sampling and data collection methodology

The NutriHeAl project was a randomized controlled trial, targeting 50 Greek municipalities, with a sample size of approximately 8000. Participants were randomized either to a group that followed a healthy Mediterranean-type diet or to a control group that received no counselling. While the project itself had its own exclusion criteria, the control group (approximately 20%) consisted of healthy individuals which represented a random sampling of the Greek population. This specific group was approached via email and asked to participate in a separate pilot study for exercise monitoring. Apart from not having a permanent or temporary condition that prevents physical activity, the only exclusion criterion specific to this study was not owning a Facebook account, or lack of willingness to create one. Following a 2-week recruitment period, a self-selecting sample of 49 Greek young adults ($n = 49$, mean age $= 24 \pm 7$ years, mean BMI $22.5 \pm 3$) was assembled. Out of the 49 participants, only 1 did not have a Facebook account and decided to create one for the pilot.

Participants were asked to record their activities on the NutriHeAl app on a daily basis, for a period of 5 weeks. Users were requested to record their exercise activities, and use the other category types of the app ('sleep', 'work', and 'other') only if desired. In addition, participants were provided with a digital pedometer (Fitbit Zip [https://www.fitbit.com/zip]) to wear all day, removing it only when in the shower or engaged in water-based physical activity (swimming etc.). The device was worn in the manufacturer-approved body locations (belt, pants pocket, bra etc. [http://help.fitbit.com/articles/en_US/Help_article/How-do-I-wear-my-Zip]). Participants were also provided with an accompanying USB adapter that, via the Fitbit software, automatically uploaded data from the pedometer to a central server.

To encourage participation and maintain users' interest, result graphs which combined Fitbit data with self-reported exercise times were released on a participant basis at the end of each week, provided that users have submitted a filled-in weekly activity diary.

In summary, data collected during the course of the pilot per user consisted of (i) a list of self-reported exercise activities with time-stamped beginning and end and (ii) Fitbit Zip data, both as overall steps/day and as specific steps/min every 1 minute, uploaded by the users automatically and downloaded centrally via the Fitbit API.

### Evaluation methodology

Even though the NutriHeAl app can collect data about many kinds of activities, the focus of this work was on collecting and evaluating the self-reported exercise activities provided and the accuracy of such an exercise monitoring methodology. In order to do that, the exercise reported by the users over the duration of the pilot can be compared with the data provided by digital pedometers such as the Fitbit Zips which were provided to participants, as they have been shown to be accurate for estimating steps during physical activity[23–27] (with restrictions, see section on limitations). Another validated digital pedometer can, of course, also be used to this effect.

To understand, for example, whether a user reporting 'running for an hour' can be taken as accurate, we can examine the steps taken according to the Fitbit during that period using a predetermined threshold of steps required for considering an activity as 'running', which we call a 'truth ceiling'. In mathematical terms, if the steps value for that duration is $X$ steps/min and the truth ceiling for the running activity is set at $Y$ steps/min, then if $X > Y$ this is a 100% accurate statement.

Naturally, this introduces the problem of how to assess the accuracy of users reporting activities with steps/min values that are 'below the truth ceiling', possibly due to over-reporting. For example, this can be a user reporting 'running for an hour' while their Fitbit Zip average steps per minute for that hour 'reports' the opposite – a value below the truth ceiling for running. One way would be to assess them as 0% accurate but since self-reported data are expected to carry some amount of noise and error, this is too penalizing. Instead, users' exercises were assessed according to how close to the ceiling they were, by employing the membership functions (m$f$) shown in Figure 3 (a concept borrowed from Fuzzy Sets theory[28]).

In practical terms, self-reported exercise activities were manually broken down to two basic categories ('low+' and 'moderate+') and two different ceilings were introduced, above which each statement was considered to be 100% accurate (or a 100% member); these were defined at 60 steps/min for low+ and at 80 steps/min for moderate+ exercise activities. Statements below these ceilings were given gradually lower membership values in the 0–100% range using a sigmoid function, to make sure that values close to the ceiling were given a fair score.

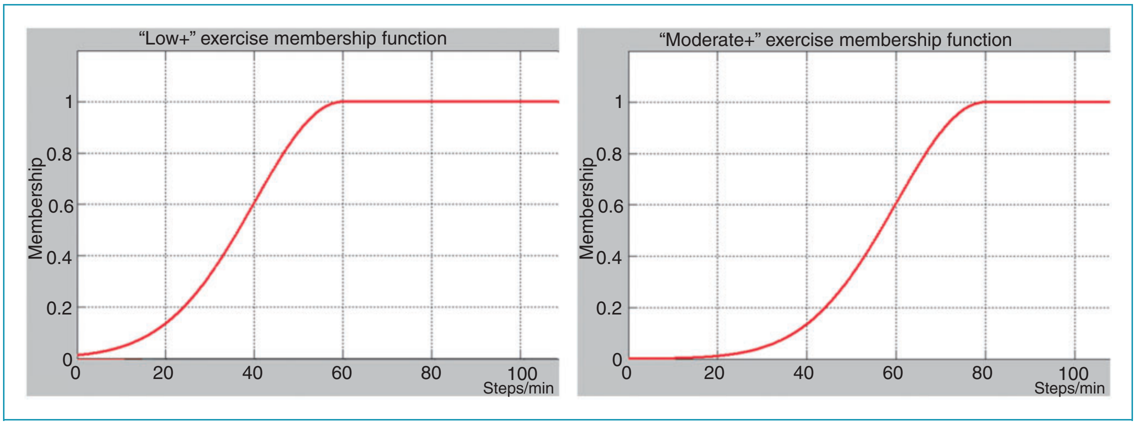


**Figure 3.** Membership functions for low+ (right) and moderate+ exercise activities (left)

These categories and ceilings were determined after consulting relevant literature[29–31] which agrees that approximately 100 steps/min can be treated as the equivalent of a moderate intensity activity and the fact that low intensity exercises such as walking lie in the 2+ MET range [https://sites.google.com/site/compendiumofphysicalactivities/Activity-Categories/walking]. Ceilings were slightly discounted to cater for the user's inexperience in providing self-reported activity data and the fact that exercise activities were not broken down into further sub-categories.

Using the above m$f$s, a statement of 'running' which corresponds to 65.9 steps/min over its duration is evaluated against the moderate+ m$f$ as 78% accurate and a statement of 'running' at 42.8 steps/min is 18% accurate. By collecting all of a user's statements about exercise activities, assessing them so and averaging them, a basic idea of a user's accuracy can be determined, and from all user's accuracy scores, the same can be done about the group and the overall data collection methodology.

## Pilot results

### *Data gathered*

A total of 44 individuals (dropout of ~10%) completed the pilot. Out of the 35 days (5 weeks) of the project's duration, activities were reported, on average, for $33 \pm 5$ days. Table 1 shows an overall view of the data gathered.

Users reported a total of 1610 exercises of which 1024 (64%) belonged to the low+ category and 586 (36%) to the moderate+ category. On average, each user submitted $37 \pm 29$ activities of which $23 \pm 23$ were in the low+ category and $13 \pm 16$ on the moderate+ category. The group's mean time of submission was $40 \pm 43$ hours after each activity. More specifically, 20% of the users reported the activity within 12 hours of its reported end, 27% within 24 hours, 25% within 48 hours and 27% after 48 hours had passed.

**Table 1.** Activities recorded by MET category, per user, and popular activities.

| NutriHeAl app data | | | |
|---|---|---|---|
| Variable | Total | % of total | Mean / user |
| Exercise (all) | 1610 | | $37 \pm 29$ |
| Low + | 1024 | 64% | $23 \pm 23$ |
| Popular low+ activities: walking (95%) | | | |
| Moderate+ | 586 | 36% | $13 \pm 16$ |
| Popular moderate+ activities: gym (18%), biking (16%), dancing (13%), running (12%) | | | |

MET: metabolic equivalent of task.

### *Evaluation result*

As discussed in the methodology section, all user-submitted exercise activities were evaluated against the membership functions for each exercise category (low+ or medium+). Table 2 shows three metrics computed from these evaluations:

– EV1: exercise reporting accuracy (ERA): Each user's exercise activities (independent of category) were evaluated and averaged to compute a user's ERA score. Afterwards, users' ERAs were averaged to compute the group's ERA.
– EV2: Low+ exercise reporting accuracy: As above, but for low+ exercise activities only

**Table 2.** Reporting accuracy by evaluation metric.

| Variable | Group total |
|---|---|
| EV1: Exercise reporting accuracy (all exercise) | 71 ± 21% |
| EV2: Low + exercise reporting accuracy | 82 ± 18% |
| EV3: Moderate+ exercise reporting accuracy | 51 ± 31% |

**Table 3.** Reporting accuracy in regard to mean time of submission.

| Time of submission (difference between activity end and report time) | Percentage of group | Accuracy score |
|---|---|---|
| Within 12 h | 20% | 84 ± 17% |
| 12–24 h | 27% | 76 ± 22% |
| 24–48 h | 25% | 75 ± 13% |
| 48 h+ | 27% | 59 ± 22% |

– EV3: Moderate+ exercise reporting accuracy: As above, but for moderate+ exercise activities only.

Table 3 shows the accuracy scores in regards to the time of submission of each exercise activity (i.e. the difference in time between the activity end and the report time).

## Discussion and future work

Users had varying reporting habits, but most reported their activity within 1 (47% of user base) or 2 (72% of user base) days of its completion. Only a handful of users (10%) reported their activities within a few hours, which is to be expected, as the motivation for each user was seeing the graphs at the end of each week. Still, their reporting frequency mimics 1-day and 3-day physical activity recall questionnaires (such as Previous Day Physical Activity Recall (PDPAR)[32] and 3DPAR[33]) which have been shown to be a valid method for physical activity recall. Out of the reported activities, two thirds were categorised as low+ exercises, of which the vast majority (~95%) were walking activities. Seeing that walking is widely reported as the most common form of physical activity,[34] we find this an expected conclusion that reflects a healthy sample.

Low+ activities were also the activity group with the highest ERA (82 ± 18%) which shows that users could, in large, accurately assess activities such as walking. The large variance in moderate + ERA scores (51 ± 31%) can possibly be attributed to the lower number of such activities present in the sample, in comparison to the low+ group (36% of total activities versus 64%, respectively). Some users reported only low+ activities while others reported both. In addition, it should be noted that using one activity m*f* for each activity category is not optimal and, ideally, each different activity should have a unique m*f*. Given the fact that research that correlates step counts to individual activities is limited, this was a best-effort approach.

In regards to ERAs over time, it is possible that viewing the results each week could influence the users and improve their accuracy over time, but after calculating each user's mean accuracy score per cycle (7 days) there was no conclusive evidence that pointed towards a statistical correlation between the weeks in the study and the accuracy score (not significant at $p < 0.05$). Seeing that the sample size (an average of $5 \times 7$-day cycles per user) is small, we believe that such an improvement may be apparent over a larger time span. The same notion was also explored for 3-day cycles but no definitive conclusion could be reached for that time span either.

Finally, as can be seen in Table 3, there is an apparent downwards trend in the accuracy scores of users in relationship to mean submission times, which speaks to the inherent 'forgetfulness' of users. However, this can easily be solved by reminders, as, for example, shown by Möller et al.[35] which use 1-day reminders. The exact time on which reminders should be sent out needs to be confirmed by further research, as our sample size is too small to draw conclusions in this regard.

In conclusion, taking the low dropout (10%) and the high number of consecutive days with recorded activities (33 ± 5) into account, reporting activities via the Facebook app was an effective, low-cost way of data collection. While the accuracy of physical activity self-reporting has been compared with objective measures before (e.g. the International Physical Activity Questionnaire (IPAQ)[36] or PDPAR[32] questionnaires), this study shows that self-reporting through a lightweight Facebook activity diary app is not only effective but also accurate when compared against an objective measure (Fitbit).

We believe that a contributing factor to this is (i) the easy way to sign up and use the app as well as (ii) the free-form text entry in combination with listing the 'recent' and 'previously-submitted' activities which has aided users in consistently providing their reports over the pilot's duration. Another important contributing factor, and the reason why, in our opinion, SNApps are a promising research tool, is the fact that users spend a lot of time on social media for their own reasons, and interacting with an app within the same environment is not a distraction. While using the app, the user has access to chat, notifications and other Facebook aspects, which helps to create the idea that he/she does not exit the platform to use the app.

### Limitations

As discussed in the previous section, the large variance in moderate+ ERA scores ($51 \pm 31\%$), can possibly be attributed to various factors (e.g. the low number of such activities present in the sample), but it can also be a result of participants' inaccuracy in reporting, the inability of the Fitbit Zip to correctly track some common activities such as biking or its moderately accurate tracking of Moderate to Vigorous Physical Activity (MVPA) in general.[37,38] Although these are not inherent limitations of SNApps and digital pedometer algorithms are getting progressively better in tracking multiple activity types, they can be a limiting factor in cases when physical activity assessment is done remotely and solely by such a tool. When the main concern is tracking moderate physical activity, SNApps should be paired with another validated self-report measure until more studies using social networks as data sources are performed.

### Future work

An important aspect of SNApps is the ability to collect social data. The existence of such data and the ease with which it can be retrieved (always according to an OSN's privacy policy) can allow for novel research approaches. For example, we plan to perform a new pilot study to associate social data with activity diaries in order to discover patterns that could link social data on Facebook with reported physical activity.

In addition, apart from being used to compute a group's overall score as was done in this study, per-person ERA scores can also be very useful; for example, users with consistently low scores could be automatically flagged by the system and excluded from results, or treated as intervention candidates.

Finally, we plan to expand this exercising monitoring scenario to a more generic lifestyle-monitoring scenario, where users report all kinds of activities via the NutriHeAl app. This will require further research into common procedures and activity types of lifestyle activities, in order to design the appropriate interfaces and reach the same level of effective data collection as was the case with this pilot study.

## Conclusions

Facebook apps are a novel, customisable and powerful tool for collecting all kinds of health data from the ever-increasing number of Facebook users. Up to now, only a handful of peer-reviewed studies have explicitly used Facebook apps for data collection in the activity monitoring space. This work presented the design and methodology of the *NutriHeAl* app which allows users to self-report their activity (duration, type) in a diary format on Facebook, which represents the first effort of its kind.

A pilot study for exercise self-reporting using this tool was presented, where a group of 49 users reported their exercise for 5 weeks while also wearing a digital pedometer (Fitbit Zip). Self-reported activities of the users were compared against the step counts as ground truth using a Fuzzy membership function approach and the user's overall ERA score was $71 \pm 21\%$. In conjunction with a low dropout (10%) and a high number of days with recorded activities ($33 \pm 5$), this novel exercise monitoring methodology can be considered an effective way of online physical activity data collection with added benefits such as low technological start-up costs and high user engagement.

Although more work is needed to treat SNApps as a validated stand-alone alternative to traditional physical activity monitoring, health professionals and researchers can use SNApps such as the NutriHeAl app to take advantage of the popularity of OSNs like Facebook for facilitating data collection in observational or intervention studies. In addition, the evaluation methodology comparing steps/min with self-reported activity can easily be modified and applied to similar e-health research.

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### References

1. Hu FB, et al. Reproducibility and validity of dietary patterns assessed with a food-frequency questionnaire. *Am J Cli Nutr* 1999; 69: 243–249.
2. Willett WC, et al. Reproducibility and validity of a semi-quantitative food frequency questionnaire. *Am J Epidemiol* 1985; 122: 51–65.

3. Bonomi AG and Westerterp KR. Advances in physical activity monitoring and lifestyle interventions in obesity: a review. *Int J Obes* 2011; 36: 167–177.
4. Duggan M, Ellison NB, Lampe C, et al. *Demographics of key social networking platforms*. Pew Research Center, November 2016, "Social Media Update 2016", http://www.pewinternet.org/2016/11/11/social-media-update-2016-methodology/ (2016, accessed: 01/10/2016).
5. Buis LR. The potential for Web-based social network sites and self-regulation for health promotion. *Am J Health Promot* 2011; 26: 73–76.
6. Wójcicki TR, Grigsby-Toussaint D, Hillman CH, et al. Promoting physical activity in low-active adolescents via Facebook: A pilot randomized controlled trial to test feasibility. *JMIR Res Protoc* 2014; 3: e56.
7. Lao LS. *Evaluation of a social networking based SNAP-Ed nutrition curriculum on behavior change*. Master Thesis, University of Rhode Island, US, 2011.
8. Valle CG, Tate DF, Mayer DK, et al. A randomized trial of a Facebook-based physical activity intervention for young adult cancer survivors. *J Cancer Surviv* 2013; 7: 355–368.
9. Cavallo DN, Tate DF, Ries AV, et al. A social media-based physical activity intervention: a randomized controlled trial. *Am J Prev Med* 2012; 43: 527–532.
10. Dishman RK and Buckworth J. Increasing physical activity: a quantitative synthesis. *Med Sci Sports Exerc* 1996; 28: 706–719.
11. Litman L, Rosen Z, Spierer D, et al. Mobile exercise apps and increased leisure time exercise activity: A moderated mediation analysis of the role of self-efficacy and barriers. *J Med Internet Res* 2015; 17: e195.
12. Foster D, Linehan C, Kirman B, et al. Motivating physical activity at work: using persuasive social media for competitive step counting. In: *Proceedings of the 14th International Academic MindTrek Conference: Envisioning Future Media Environments [Internet]*. New York, NY, USA: ACM, 2010, pp. 111–116 (MindTrek '10).
13. Maher C, Ferguson M, Vandelanotte C, et al. A web-based, social networking physical activity intervention for insufficiently active adults delivered via Facebook app: Randomized controlled trial. *J Med Internet Res* 2015; 17: e174.
14. Kernot J, Olds T, Lewis LK, et al. Usability testing and piloting of the mums step it up program – a team-based social networking physical activity intervention for women with young children. *Plos One* 2014; 9: e108842.
15. AIHW 2003. The Active Australia Survey: a guide and manual for implementation, analysis and reporting. Cat. no. CVD 22. Canberra: AIHW, http://www.aihw.gov.au/publication-detail/?id=6442467449 (2003, accessed 1 October 2016).
16. Ding D, Ayubi S, Hiremath S, et al. Physical activity monitoring and sharing platform for manual wheelchair users. In: *Engineering in Medicine and Biology Society (EMBC), 2012 Annual International Conference of the IEEE*, San Diego, CA, USA, 28 August 2012, pp. 5833–5836. IEEE.
17. Pagkalos I and Petrou L. Using social network apps as social sensors for health monitoring. In: *XIII Mediterranean Conference on Medical and Biological Engineering and Computing*, Seville, Spain, 25–28 September 2013, pp. 1330–1333. Cham: Springer.
18. Pagkalos I, Rossiou D and Papadopoulou S. Monitoring physical activity through social networks: a Facebook case study. In: *6th DIETS/EFAD Conference*, Portoroz, Slovenia, 2012, http://www.efad.org/everyone/3209/5/0/32.
19. Pagkalos I and Petrou L. SENHANCE: A semantic Web framework for integrating social and hardware sensors in e-health. *Health Inform J* 2016; 22: 505–522.
20. Schofield WN. Predicting basal metabolic rate, new standards and review of previous work. *Hum Nutr Clin Nutr* 1985; 39(Suppl. 1): 5–41.
21. World Health Organization. The world health report 2000 – Health systems: improving performance, http://www.who.int/whr/2000/en/ (2000, accessed 1 October 2016).
22. Ainsworth BE, et al. 2011 compendium of physical activities: a second update of codes and MET values. *Med Sci Sports Exerc* 2011; 43: 1575–1581.
23. Noah JA, Spierer DK, Gu J, et al. Comparison of steps and energy expenditure assessment in adults of Fitbit Tracker and Ultra to the Actical and indirect calorimetry. *J Med Eng Technol* 2013; 37: 456–462.
24. Diaz KM, et al. Fitbit: An accurate and reliable device for wireless physical activity tracking. *Circulation* 2015; 131(Suppl. 1): AMP11–AMP11.
25. Tully MA, McBride C, Heron L, et al. The validation of Fitbit Zip$^{TM}$ physical activity monitor as a measure of free-living physical activity. *BMC Res Notes* 2014; 7: 952.
26. Kooiman TJM, Dontje ML, Sprenger SR, et al. Reliability and validity of ten consumer activity trackers. *BMC Sports Sci Med Rehabil* 2015; 7: 24.
27. Schneider M and Chau L. Validation of the Fitbit Zip for monitoring physical activity among free-living adolescents. *BMC Res Notes* 2016; 9: 448.
28. Zadeh LA. Fuzzy sets. *Inf Control* 1965; 8: 338–353.
29. Marshall SJ, et al. Translating physical activity recommendations into a pedometer-based step goal: 3000 steps in 30 minutes. *Am J Prev Med* 2009; 36: 410–415.
30. Harrington DM, Dowd KP, Tudor-Locke C, et al. A steps/minute value for moderate intensity physical activity in adolescent females. *Pediatr Exerc Sci* 2012; 24: 399–408.
31. Pillay JD, Kolbe-Alexander TL, Proper KI, et al. Steps that count: physical activity recommendations, brisk walking, and steps per minute-how do they relate? *J Phys Act Health* 2014; 11: 502–508.
32. Trost SG, Ward DS, McGraw B, et al. Validity of the Previous Day Physical Activity Recall (PDPAR) in fifth-grade children. *Pediatr Exerc Sci* 1999; 11: 341.
33. McMurray RG, et al. Comparison of two approaches to structured physical activity surveys for adolescents. *Med Sci Sports Exerc* 2004; 36: 2135.

34. Siegel PZ, Brackbill RM and Heath GW. The epidemiology of walking for exercise: implications for promoting activity among sedentary groups. *Am J Public Health* 1995; 85: 706–710.
35. Möller A, Kranz M, Schmid B, et al. Investigating self-reporting behavior in long-term studies. In: *ACM SIGCHI Conference on Human Factors in Computing Systems*, Paris, France, 27 April–2 May 2013, pp. 2931–2940. ACM.
36. Booth ML, et al. International physical activity questionnaire: 12-country reliability and validity. *Med Sci Sports Exerc* 2003; 195: 3508–1381.
37. Evenson KR, Goto MM and Furberg RD. Systematic review of the validity and reliability of consumer-wearable activity trackers. *Int J Behav Nutr Phys Act* 2015; 12: 159.
38. Ferguson T, Rowlands AV, Olds T, et al. The validity of consumer-level, activity monitors in healthy adults worn in free-living conditions: a cross-sectional study. *Int J Behav Nutr Phys Act* 2015; 12: 42.