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Activity Trackers: A Critical Review

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Abstract. The wearable consumer health devices can be mainly divided into activity trackers, sleep trackers, and stress management devices. These devices are widely advertised to provide positive effects on the user's daily behaviours and overall heath. However, objective evidence supporting these claims appears to be missing. The goal of this study was to review available evidence pertaining to performance of activity trackers. A comprehensive review of available information has been conducted for seven representative devices and the validity of marketing claims was assessed. The device assessment was based on availability of verified output metrics, theoretical frameworks, systematic evaluation, and FDA clearance. The review identified critical absence of supporting evidence of advertised functions and benefits for the majority of the devices. Six out of seven devices did not provide any information on sensor accuracy and output validity at all. Possible underestimation or overestimation of specific health indicators reported to consumers was not clearly disclosed to the public. Furthermore, significant limitations of these devices which can be categorized into user restrictions, user responsibilities and company disclaimers could not be easily found or comprehended by unsophisticated users and may represent a serious health hazard.

Keywords. Consumer health informatics, activity tracker, validity, review

Introduction

One of the key emerging trends in consumer heath informatics found in the resent review [1] was the expansion of mobile health applications [2]. Mobile applications facilitating patient-centered care and supporting self-monitoring using wearable devices are expected to form a new market niche exceeding $30 billion in 2018 [3]. In line with this outlook, growing number of companies consisting of small start-ups and well established manufacturers are hastily entering the wearable fitness app market. In terms of technology, this boom in wearable health apps has been triggered by the widespread availability of inexpensive micro-electro-mechanical systems (MEMS) sensors used, for example, for accelerometers and gyroscopes. Meanwhile, a variety of new brands of wearable devices are being aggressively advertised and sold as effective means to improve users' activity, sleep, and overall health. These devices are aimed at encouraging general population including seniors to make daily efforts to manage their health especially in the domains of activity, sleep and stress. An underlying promise to an unsophisticated consumer is that for a price of a wearable device and online subscription to a health tracking website, the user's health behaviours will be positively affected and overall heath will be improved. However, supportive evidence and systematic evaluation of these claims appears to be missing. The goal of our project was to review availability of objective information on performance of wearable devices

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sold in the market and validity of marketing claims. In this article, as a part of this work, we present our review results related to wearable activity trackers.

1. Methods

Seven wearable activity trackers were selected: BodyMedia FIT, Fitbit Flex, Jawbone UP, Basis band, Polar Loop, Nike+ FuelBand and Scosche RHYTHM. Comprehensive literature and online search was conducted using set of keywords including product name, associated technological terms, and company names in PubMed, FDA's database, and Google Scholar as well as in the vendors' own websites and linked webpages.

2. Results

2.1. Metrics

Seven activity trackers are categorized in two groups: six devices with an accelerometer and one device without an accelerometer (Scosche RHYTHM) which utilizes an optical heart beat detection sensor instead. Six activity trackers with an accelerometer are again divided into four devices (Fitbit Flex, Jawbone UP, Polar Loop and Nike+ FuelBand) embedding an accelerometer solely and two devices (BodyMedia FIT and Basis band) embedding other sensors also as like skin temperature sensor, Galvanic Skin Response (GRS) sensor, electrical/optical heart beat detection sensor and heat flux sensor. In case of Polar Loop, to get more accurate energy estimation, Polar Heart rate sensor can be worn on the chest additionally. The accuracies of sensors adopted in BodyMedia FIT are reported to be high enough (Accelerometer: ±0.08g; Heat Flux: ±10.0W/m^2; GSR: ±9.0nS; Skin Temperature: ±0.8°C). However, any sensor accuracy of the other activity trackers cannot be found. All seven activity trackers provide 'Calories burned' metric and six activity trackers with an accelerometer commonly provide 'Steps taken' metric as well. Accelerometer embedded activity trackers also produce 'Distance traveled', 'Exercise intensity', 'Very active minutes', and/or 'Longest active minutes' metrics. Basis band and Nike+ FuelBand can display additionally 'Perspiration' and 'Temperature' metrics and 'Nike Fuel earned' metric, respectively. In case of Scosche RHYTHM, by deploying a GPS sensor of a smartphone, it provides 'Distance traveled' and 'Speed and pace' metrics. Only a BodyMedia FIT is found to reveal its metric accuracies of 'Total calories burned', 'Total minutes of exercise' and 'Total steps taken'. No other devices report the accuracies of their metrics representing any aspect of physical activity.

2.2. Use of evidence-based methodologies in activity trackers

Since the first micro-electromechanical system (MEMS) accelerometer came into the world [4], a variety of wearable systems embedding a MEMS accelerometer for physical activity monitoring have been studied. Contrary to a pedometer bearing a drawback to estimating activity intensity, an accelerometer was established to be able to pick up acceleration proportional to external force reflecting activity intensity and subsequently energy expenditure (EE). In 1995, Melanson and Freedson reported that, in a laboratory setting, a linear regression model involving body mass and activity counts measured from a single accelerometer worn on wrist was able to predict actual EE with standard error of estimate of $1.05 Kcal \cdot min^{-1}$ while showing correlation coefficient of 0.85 between actual and estimated EEs [5]. Regarding EE estimation in free-living condition, Bouten et al. [6] reported a correlation coefficient of 0.89 for 13 subjects asked to perform standardized daily physical activity for 36 hours but Hendelman et al. [7] reported correlation coefficients of 0.59~0.62 for 25 subjects asked to complete four bouts of walking at self-selected speeds, to play two holes of golf, and to perform indoor and outdoor household tasks. The latter's relatively low correlation was inferred to be caused by the inability of accelerometers to detect energy consumption related with upper body movement. BodyMedia FIT and Basis band contain more sensors on top of an accelerometer in order to compensate for the limitation of an accelerometer in determining activity intensity. According to the study performed by St-Onge et al., SenseWear Pro Armband, which utilizes the same sensors and the same measuring principle to BodyMedia FIT, showed relatively high correlation coefficient of 0.81 between its estimated EE and measured EE by the doubly labeled water (DLW) method in 45 free-living adults [8]. However, neither BodyMedia FIT nor SenseWear Pro Armband has unveiled any detailed explicit methodology to calculate metrics and it's the same to Basis band. Scosche RHYTHM, which does not rely on an accelerometer, also has not revealed the theoretical background. This device is assumed to be based on the relationship between EE and accumulated or averaged heart rate over a specific period [9-10]. For three different levels of stead-state activities on either a treadmill or a cycle ergometer, the correlation coefficient between measured EE and estimated EE with a regression model involving gender, heart rate, weight and age was found to reach as high as up to 0.857 [11]. However, for sixteen different activities simulating free-living conditions, the EE estimation with minute-by-minute heart rate plus basal metabolic rate was reported to be inaccurate; inter-individual coefficient of variance were 14~18% and estimation error of EE in one individual was predicted to range from -2986 to 2738 kJ/16h [12]. Overall, the majority of activity trackers lacked sufficient information on methodologies they employed and evidence of their efficacy.

2.3. Evaluation works

We also looked into whether each device has any published articles dealing with evaluations performed in scientific and controlled manners. As a result, there were found several published articles for SenseWear Armband and its latter models (Pro and Pro3) [13-18]. The SenseWear Armband or latter model was evaluated mainly by comparing estimated EE with the true value measured by indirect calorimeters or DLW method. The armband was shown to bring out valid and reliable estimation for free-living EE ($r=0.81$; $P<0.01$) [13] and resting EE ($r=0.86$; $P<0.0001$, $r=0.76$; $P<0.004$) [14-15] and, in laboratory exercise conditions, was proved to result in the best estimate of total EE at most speeds compared to CSA (Computer Science Applications Inc., Shalimar, FL), TriTrac-R3D (Professional Products Inc., Madison, WI), RT3 (Stayhealthy Inc., Monrovia, CA) and BioTrainer-Pro (IM Systems, Baltimore, MD) [16]. However, it also was found that SenseWear Pro Armband could significantly underestimate or overestimate total energy expenditure depending on the intensity and type of an exercise [17] and that SenseWear Pro3 Armband could not estimate EE within 16% error of the criterion for nine of the eighteen activities, consisting of six indoor home-based activities, six miscellaneous activities and six outdoor aerobic activities [18]. One of Fitbit's family models (Ultra and One) and Nike+ FuelBand were found to be evaluated crudely in a few published articles [20-21]. Guo et al. compared Fitbit One, Nike+ FuelBand, iPhone Moves App and pedometers with actual steps taken over 400m distance and measured by a mechanical clicker, they reported that Fitbit One and Nike+ FuelBand showed 1.05±2.26% and 7.79±9.17% of estimation errors, respectively [19]. When Fitbit Ultra and Nike+ FuelBand were applied to people with Stroke and Traumatic Brain Injury, Fitbit Ultra and Nike+ FuelBand resulted in 0.73 (mean difference=-9.7) and 0.20 (mean difference=-66.2) of the intra-class correlation coefficients between actual steps retrieved from video tape and estimated steps, respectively [20]. Jawbone UP was found in a single article whose purpose was to evaluate and compare the accuracy of activity trackers including Nike+ FuelBand, Fitbit Ultra, BodyMedia FitCore and Adidas MiCoach as well as Jawbone UP in terms of steps taken and calories burned [21]. According to the results of the study, the accuracies of all trackers seemed good for steps taken but relatively low for calories burned. The accuracy of trackers, even of BodyMedia FIT, varied widely depending on the exercise modality. In case of Polar Loop and Scosche RHYTHM, there could not find any published scientific article.

2.4. FDA clearance

Only BodyMedia FIT was confirmed to be registered with the U.S. Food and Drug Administration (FDA) as a medical device for isokinetic testing and evaluation.

3. Discussion

First of all, most critical issues found in the devices are questionable or unverified qualities or benefits. Even with seductive claims or testimonies floating over internet, all the companies except BodyMedia do not provide the information on accuracies of sensor(s) and metrics sufficiently or at all. Similarly, only BodyMedia was found to have some published evaluation works supporting the device's reliability. However, even in case of BodyMedia, the disappointing facts are not well-known to general users that it is likely to underestimate total energy expenditure significantly for walking exercise, cycle ergometry and stepping exercise and overestimate total energy expenditure significantly for arm ergometer exercise [17]. It is also apt to result in up to 74% of errors in estimating EE for half of eighteen daily activities [18]. On the other hand, according to a third-party report [21], Nike+ Fuelband, Fitbit Ultra and Jawbone UP showed 0.98, 0.55 and 0.99 of correlations between estimated and actual steps for treadmill walking; 0.99, 0.98 and 0.44 for treadmill running; 0.99, 0.97 and 0.99 for elliptical exercise; 0.34, 0.17 and 0.49 for agility exercise. As a result, the correlations between estimated and measured EEs were limited to 0.24~0.87 for treadmill walking, 0.63~0.72 for treadmill running, 0.08~0.41 for elliptical exercise and 0.47~0.67 for agility exercise. These kinds of information should be disclosed to the public in order to help users understand the technical limitations of the devices before purchasing them. There is another serious issue called the self-imposed limitations which the companies notify through their terms of use, conditions for web services, user manuals, user guide, legal notice or similar but a user hardly recognize. The self-imposed limitations can be categorized into three types; user restriction, user responsibility and company disclaimer. According to these limitations, 1) some users are not allowed to use some of the devices because of their age or medical and nutritional conditions; 2) users should consult a physician or a qualified medical professional before starting a fitness program or dietary program and could be responsible for all risks involved with the provided services; 3) companies may not be responsible for any risks or any information and services and would not guarantee the device output accuracy, reliability or effectiveness of their services and devices. Inability to access and comprehend these limitations represents a serious health hazard for consumers.

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