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Validating a commercial device for continuous activity measurement in the older adult population for dementia management

Tanvi Banerjee[a,*], Matthew Peterson[b], Quintin Oliver[a], Andrew Froehle[b,c], Larry Lawhorne[b]

[a] Department of Computer Science and Engineering, Wright State University, 303 Russ Engineering Building, 3640 Colonel Glenn Highway, Dayton, OH 45435, USA
[b] Boonshoft School of Medicine, Wright State University, USA
[c] Department of Kinesiology and Health, Wright State University, USA

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ABSTRACT

With the introduction of the large number of fitness devices on the market, there are numerous possibilities for their use in managing chronic diseases in older adults. For example, monitoring people with dementia using commercially available devices that measure heart rate, breathing rate, lung volume, step count, and activity level could be used to predict episodic behavioral and psychological symptoms before they become distressing or disruptive. However, since these devices are designed primarily for fitness assessment, validation of the sensors in a controlled environment with the target cohort population is needed. In this study, we present validation results using a commercial fitness tracker, the Hexoskin sensor vest, with thirty-one participants aged 65 and older. Estimated physiological measures investigated in this study are heart rate, breathing rate, lung volume, step count, and activity level of the participants. Findings indicate that while the processed step count, heart rate, and breathing rate show strong correlations to the clinically accepted gold standard values, lung volume and activity level do not. This indicates the need to proceed cautiously when making clinical decisions using such sensors, and suggests that users should focus on the three strongly correlated parameters for further analysis, at least in the older population. The use of physiological measurement devices such as the Hexoskin may eventually become a non-intrusive way to continuously assess physiological measures in older adults with dementia who are at risk for distressing behavioral and psychological symptoms.

1. Introduction

The number of devices that have been connected via the Internet, increased from around 200 million in 2000 to approximately 10 billion today, moving us from the age of the Internet of Things (IoT) towards the confluence of people, process, data, and things—the Internet of Everything (IoE) (Cisco's). More emphasis is being placed on pushing the field forward from data towards knowledge by extracting meaning from data that assists in actionable information. Advancements in mobile health technologies (Banerjee & Sheth, in press) adds the IoE dimension to healthcare innovations bringing to attention the numerous commercial devices available in the

* Corresponding author.
E-mail addresses: tanvi.banerjee@wright.edu (T. Banerjee), matthew.peterson@wright.edu (M. Peterson), oliver.66@wright.edu (Q. Oliver), andrew.froehle@wright.edu (A. Froehle), larry.lawhorne@wright.edu (L. Lawhorne).

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market. Devices created by manufacturers including Fitbit, Jawbone, Garmin, Apple, and others have made physiological and activity information readily available to the public, as well as opened up a new world for continuous activity monitoring to manage chronic healthcare conditions. However, this also brings the challenges of ensuring that the sensor readings are accurate and sensitive enough for chronic disease management. This is crucial not only for ensuring the generalizability of a sensor within a target population, but also its capability to measure the *day-to-day variability* in measurement that can be corroborated with the symptoms pertaining to the chronic health condition. The aim of this study is to validate the parameters measured by the Hexoskin vest sensor against clinically established gold standard measures (clinically established ground truth measures (Versi, 1992)) with 31 older adults in order to check the feasibility of using the vest with the older adult population.

2. Background

Studies described in Zisberg, Young, and Schepp (2009), Clark et al. (2001) indicate the importance of longitudinal analysis of the daily routine of older adults to detect anomalies or deviations in their usual patterns using automated, non-intrusive methods. Moreover, analyzing physiological measures such as heart rate and breathing rate can also provide critical insights to the person's stress levels and physical activity (Understanding the stress response). In order to detect these deviations, the instruments or the sensors must be validated prior to use in healthcare settings.

In Swartz et al. (2009) attempted to extract the energy expenditure from physical activity measured using motion sensor devices (Omron pedometer (OM), Sportbrain pedometer (SB), and Kenz Life-Corder (LC) accelerometer). One interesting observation from the study was that the motion sensors performed accurately at higher speeds, with lower accuracies at lower speeds. This was not surprising given their primary uses as fitness devices. What was surprising in this study was that energy expenditure was not measured well in either the normal body mass index (BMI $< 25.0\ \text{kg m}^{-2}$) or obese participants (BMI $\geq 30.0\ \text{kg m}^{-2}$), but performed well in overweight participants (BMI between 25.0 and $30.0\ \text{kg m}^{-2}$), particularly the SB sensor, which had the highest performance. The LC sensor performed poorly across all participants, with the OM having a better performance than LC, but poorer than SB. The results highlighted performance differences across the different sensors in measurement of energy expenditure. In Diaz et al. (2016) validated the use of Fitbit One to measure step count and energy expenditure in female adults. Here, different gait speeds were tested with 13 participants, and across Fitbit devices placed on the torso, hip, as well as wrist. While the step counts were strongly correlated across the devices, the error in energy estimate varied from 9% to 19% for the device placed on the torso, with lower performance for the other locations.

In Takacs et al. (2014), the authors compared the performance of three Fitbit One devices against one another to measure the inter-reliability of the devices in 30 healthy adults. The trackers were placed on both of the hips, and one in the shirt pocket. Using the step count metric, no significant difference was found across the three devices, with high inter-device reliability. In another study in Price et al. (2016), three different devices, Fitbit One, Jawbone Up, and Garmin Vivofit were used to measure two different activities running and walking for 14 adults. Energy expenditure was compared across the trackers and was validated against indirect calorimetry values for the participants. Their study showed less promising results, as the devices were found to be unsuitable as research measurement tools for recording precise and accurate energy expenditure estimates. However, the authors discussed the potential of using these devices in interventions of behavior change as they can provide estimates of relative changes in energy expenditure that allow users to understand activity patterns on an ongoing basis.

In our earlier study, we investigated the use of a fitness vest, the Hexoskin sensor as a tool for use in dementia care and management (Banerjee, Anantharam, Romine, Lawhorne, & Sheth, 2015). Specifically, we used a smaller group of adults where 4 participants were of ages 30–35 years, and 3 healthy older adults of age ~ 60 years as the preliminary study cohort. In the Hexoskin sensor, five parameters are measured: cadence (in steps per minute), activity level (net acceleration in units of g), heart rate and breathing rate (in beats per minute), and minute ventilation (in mL per minute). Gait-related activities were validated for the cadence measure, and the remaining parameters were compared with the cadence using multivariate analysis. This initial study indicated that for the diverse population across different activities, the cadence, activity level, breathing rate and minute ventilation were strongly correlated with one another.

In all the studies described above, the devices were analyzed specifically to understand their potential for use with the healthy population. However, in chronic disease management applications, specific target groups need to be investigated as discussed in the review paper by Remoortel et al. (2012), which reviewed the use of activity monitors across different studies. The authors found that most of the studies conducted included only healthy cohorts (118 out of 134). They further cautioned against the use of activity monitors in chronic healthcare settings without a proper validation study, since activity monitors are less accurate at slow walking speeds, and need further examination prior to use in clinical trials (Fig. 1).

In this study, we expand the scope of our previous analysis (Banerjee et al., 2015) to the older adult population of age 65 years and older with mobility impairment, cognitive impairment, neither, or both, using participants from the Fels Longitudinal Study (study population described in detail in Section 3 of this manuscript).

Specifically, we ask the following research questions:

(i) What are the relationships between the different phenotype measures (such as demographic information on age, gender, ethnicity, cognitive status) in our study cohort? What are their similarities and differences?
(ii) How do the Hexoskin sensor readings compare to gold standard measures in terms of accuracy, precision, and bias?